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Decentralized Economic Dispatch for Radial Electric Distribution Systems

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Decentralized Economic Dispatch for Radial Electric Distribution Systems

by

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Submitted to the Institute for Data, Systems, and Society
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Abstract

Electricity power systems, typically a very slow-moving and traditional industry, is in a state of flux as technological innovations, such as rooftop solar, home energy management systems, and electric vehicles, are being rapidly integrated into electric distribution systems. As the need to decarbonize the electricity sector becomes increasingly important, a distribution system operator could serve a useful purpose by operating distribution systems and acting as the market operator at a sufficiently granular level to potentially improve resiliency, decrease delivery losses, and send appropriate price signals to its customers. Currently, this latter functionality is assumed to be done using centralized economic dispatch. Given a very large number of small customers and their diverse preferences, it would be computationally expensive to implement centralized economic dispatch at the distribution level with perfect information.

In this thesis, an alternative algorithm, referred to as decentralized economic dispatch, is introduced which dispatches power for radial electric distribution systems while accounting for heterogeneous demand functions across customers, demonstrating computationally feasibility, and respecting the physical limits of the system. Unlike other approaches proposed in literature, which often take many iterations or do not converge, the algorithm introduced here converges to the same solution as a centralized operator with perfect information, and does so with only two sweeps across the system. A proof-of-concept example on a 46-bus system demonstrates the physical and economic benefits of the distributed algorithm with varying levels of distributed energy resources.

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Chapter 1

Background

Electricity has certain characteristics which make it a unique product to purchase and sell. Along with other forms of energy, electricity has a very inelastic demand function, meaning that the quantity demanded does not fall much when prices are high. Everybody in the developed world consumes electricity, yet customers typically do not have a clear estimate of how much electricity they consume per day, the price per unit of electricity, or the proper units used to measure electricity. Another way in which electricity varies from other products is that the time between generation and consumption is very short, which will remain imperative until energy storage technologies become more affordable and accessible. This is becoming increasingly relevant with variable renewable energy generation, such as wind and solar energy, which provides a level of intermittency that adds uncertainty to the system.

Presently, electricity service to small urban customers is done by providing sufficient generation through the transmission/sub-transmission networks to the points of contacts (feeders) which further distribute power to the customers via a distribution grid. The distribution grid is sized to support peak historic electricity use. Currently, power is not dispatched individually to the small end users. Instead, whatever is consumed gets provided according to basic physical power flow laws. Recently, distribution companies are considering the implementation of distribution control centers so that power is dispatched in a more granular way to the customers. The potential role of a distribution system operator in the future is discussed in **Chapter 2**, followed by a discussion surrounding energy transactions in **Chapter 3**. Dispatching power could be implemented using centralized economic dispatch, much the same way as it is done in the control centers of transmission/sub-transmission systems at present. An alternative approach to centralized economic dispatch is proposed and it is described in **Chapter 4**. This algorithm is fundamentally decentralized, and it requires only minimal communications among the end users. It is shown to converge to the same solution as the centralized economic dispatch which requires perfect information and would be complex to implement in urban areas with very large number of customers. The economic implications of said algorithm are then explored further in **Chapter 5**. The concluding remarks include the open questions for future work and the relevance of the proposed concepts in **Chapter 6**.

1.1 Basics of Power Systems

There are four relevant stages of power systems between the point where electricity is generated and the point where a light switch is turned on: electricity generation, transmission, distribution, and retailing.

Generation The first stage, energy generation, was traditionally provided by a centralized energy producer, such as a power plant. While centralized generators used to be the main contributor to the energy generated for the electricity grid, there has been a heightened appearance of Independent Power Producers (IPPs). They either sell the electricity to the utilities, or directly to consumers. Both centralized generators and IPPs have a substation nearby to perform a voltage transformation of raising the voltage before the energy is transported across the transmission system.

Transmission Systems The next stages of the electricity sector, electric power transmission and electric power distribution, make up the traditional 'electric grid.'

Power is transmitted across large distances in high voltage in order to prevent losses. Low-voltage lines lose more energy across distances than high-voltage lines. The transmission system has High-Voltage (HV), between 110 kV and 230 kV, and Extra High-Voltage (EHV) lines, which transmit energy from the generator to a centralized substation or switching station, or a location closer to the consumer (Beaty, 1998). After transmitting power across long distances, typically with overhead transmission lines, it reaches another substation where the voltage is lowered before the energy is transmitted to the distribution lines. These substations are typically located closer to where the energy is consumed, such as in cities, towns, or large industrial sites. When the system expands or the existing infrastructure is insufficient, the industry typically builds new transmission lines with higher voltage rather than upgrading the existing infrastructure, which is why multiple transmission lines can be seen next to one another in the countryside. A very basic rendition of the different stages of power systems is displayed in Figure 1-1.

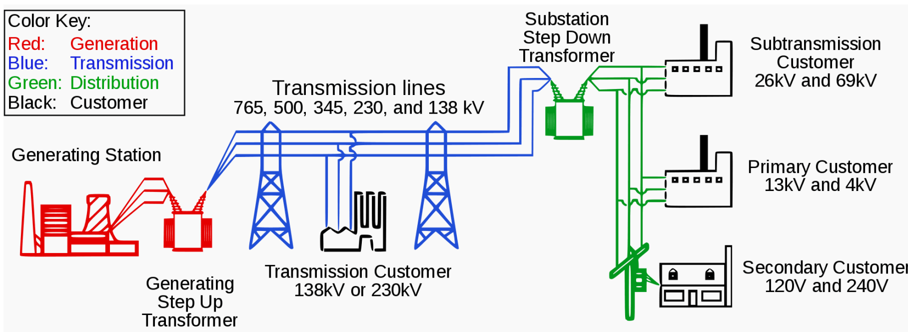


Figure 1-1: Power Systems Schematic (Csanyi, 2017)

Distribution Systems Distribution systems include the rest of the components which bring the electricity from the transmission lines to the end user. The bulk power substation receives electricity from the transmission system as it lowers the voltage, and transmits the power to the sub-transmission systems, which bring power to the distribution substations (Beaty, 1998). The distribution substations are strategically located closer to residential, commercial, and industrial customers, and step the voltage down to a lower level. From the distribution substation, the electricity goes across the wires of primary feeders until it reaches the distribution transformer, which performs the final voltage transformation down to levels that the consumer will receive. The secondary circuits include the wires that connect the distribution transformer with the end customer, such as the three phase feeder connecting the substation to houses. The process described here is typical for residential customers, but some industrial customers may build their own substations so that they can obtain the electricity at a higher voltage thus with less losses, and at a better rate (Beaty, 1998).

There are several different geometries of how distribution systems could be designed. For residential purposes, the distribution system often has a radial, or tree-like, structure, as displayed on the left side of Figure 1-2. While radial structures are not as reliable as a meshed grid geometry, it is of considerably lower cost and typically used in suburban neighborhoods. Meshed grids are used in dense, urban centers, and the wires are often underground, which increase the upfront costs. However, if something goes wrong in between the substation and the first three-phase switch of a meshed grid, it will likely lead to a power outage for all of the customers that are connected to that portion of the distribution circuit (Beaty, 1998).

Overall, electricity distribution systems are very important; almost 90% of power outages in the United States are caused by problems with the distribution system equipment. These issues could be caused by natural disasters or more commonly: car crashes, trees, animals, or aging infrastructure.

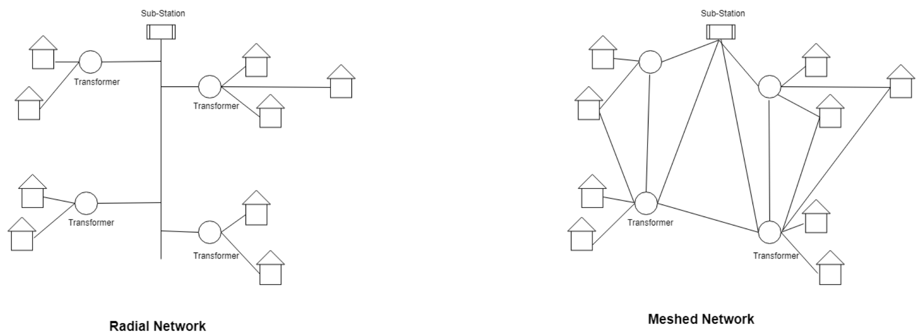


Figure 1-2: Radial and Meshed Networks

Retailing The fourth and final stage of electricity delivery is electricity retailing, which involves all the front-end interaction with the customers such as billing, customer acquisition, etc. This stage has drastically changed over the past few decades, as described in Section 1.3. While a centralized utility company used to handle the electricity transmission, distribution, and retailing, essentially making up a vertically integrated monopoly, the system has undergone a large transformation. Ideally, the restructured energy industry invites news actors to enter the market and the competition would improve efficiency and encourage innovation in the industry, though this is rarely seen in practice.

1.2 Electricity Regulation

The technical aspects, economic constraints, and regulatory structure are all very important and interrelated when analyzing power systems. When proposing an alternative way of operating power systems, it is important to understand which regulator has the authority over which respective jurisdiction, and could potentially implement an innovative approach or a new policy.

1.2.1 Electricity Regulators

Energy policies of the United States vary regionally; there are many different regulatory agencies at the national, state, and local levels, which makes it difficult to pass innovative policies that remain consistent with one another. It is important to understand which regulatory bodies have jurisdiction in different regions, and how decision makers collaborate with one another in order to make a sustainable difference in the infrastructure, the market structure, and energy policy. Here, we will mostly focus on the United States, with a few comments on the electricity regulation of other countries.

At the US federal level, the Department of Energy oversees policies, research, and writes legislation on a variety of areas related to energy; from energy conservation policies to energy-related research to the nuclear weapons program. Federal Energy Regulatory Commission (FERC) is the federal agency that regulates electricity transmission and the wholesale electricity markets. FERC's role is more important for interstate commerce and for setting federal regulations regarding wholesale competition. In theory, FERC should be able to help with the improvement of the interstate infrastructure, and monitor the electricity sales in order to prevent predatory pricing and other anti-competitive behavior. Another important role that FERC plays is regulating Power Purchase Agreements (PPA's), which are essentially contracts between an energy producer and buyer. These contracts are increasingly important for the sale of renewable energy such as solar, wind, fuel cells, and other power sources produced by IPPS.

At the state level, the Public Utilities Commission (PUC), also known as a utility regulatory commission, is responsible for the regulation of public utilities including water, gas, and electricity. The PUC's duties include regulating and monitoring the service and prices announced by the utilities companies. Some towns or cities have a similar regulatory figure for their own municipality.

Who sets the standards? In addition to the regulatory bodies, the important industry-specific organizations include the American National Standards Institute (ANSI) and the Institute of Electrical and Electronics Engineers (IEEE).

ANSI is a private non-profit organization that sets US standards such that products of the United States are compatible with international products. ANSI determines the voluntary consensus standards for most products, processes, and systems across the United States, including electricity and power systems. IEEE is a professional association of experienced and expert electrical engineers across the world. They post publications, give awards and medals, organize conferences, and have technical societies, technical councils and technical committees. One of the organizations within IEEE, the IEEE Standards Association, set global standards for various areas including power systems, information technologies, and microgrids.

1.3 Restructuring of the Electricity Industry

Electricity was typically supplied by a vertically integrated energy company up until the industry was restructured in the late 20th century. The following sections include a description of the electricity industry both before and after their restructuring, and the benefits and disadvantages of both models.

1.3.1 Electricity Industry prior to Restructuring

Initially, all four stages of the electricity system were operated by a vertically-integrated utility company. Thus, regulatory agencies had to ensure that the natural monopolies were providing affordable access to these goods. Electric power distributors were considered natural monopolies because it was more cost-effective for a single producer to provide these public goods to the consumers rather than having a competitive market, due to the high startup costs, scale effects, and other barriers for market-entry (Viscusi, 2009). Some utilities were state-owned, while others were owned by investors. If the utilities company was privately owned, then a third-party regulator had to protect the consumer's welfare, by monitoring product quality and limiting producer profit (Perez-Arriaga, 2016).

There are several benefits and disadvantages associated with regulated electricity markets. For example, delegating the responsibility of building and maintaining the transmission and distribution lines to a single entity is advantageous due to the economies of scale of the infrastructure. Essentially, it does not make sense to have multiple transmission lines delivering electricity to the same neighborhood because it is both economically and technologically inefficient. This scale effect prevents other actors from easily entering the electricity sector. In addition to economic efficiency, there are technical advantages associated with centralized coordination of the system. If there are many energy generators supplying to the grid without coordination, this could lead to congestion along the transmission system, which would place strain on the grid and could ultimately lead to blackouts.

From an economic perspective, the vertically-integrated monopolies could contribute to economic efficiency within the four different parts of the electricity sector. In theory, if the generation, transmission, distribution, and retail was done by four separate parties, then the transaction costs to compromise an efficient outcome could be financially expensive and could require a lot of time for negotiations.

The obvious fear with a monopoly, even a regulated natural monopoly, is that the single producer can raise prices, especially for such an inelastic good. According to the Federal Power Act of 1935, FERC was responsible for assuring that the price paid by the consumer was fair, and that the natural monopoly is not obtaining an outrageous margin of profits with the sale of a basic necessity.

The regulatory agencies used rate-of-return regulation to limit the profits made by the monopolies. 1.1 was used to implement rate-of-return regulation, where n is the number of services, s represents the "fair" rate of return, B is the rate base, and the expenses refer to operating costs and other costs subjected to the energy provider (Viscusi, 2009).

$$\sum_{i=1}^{n} p_i q_i = Expenses + sB \tag{1.1}$$

In theory, the regulating agency is trying to set the price of electricity to correspond to the price of electricity if the industry was a fully competitive market. However, this process was subjected to several difficulties, namely asymmetric information for the regulators. There are many unknown variables in this equation; the regulators must estimate the total expenses that are inflicted upon the utilities companies, the quantity of energy used is highly variable, and it is difficult to decide upon a fair amount of profit for the utility company. If the rate of returns is too low, then the utility company would not be able to invest in upgrading the system or address necessary repairs. However, if the 'sB' term of the equation is too high, and the monopolists are obtaining a high rate of return, then they have no incentive to invest in long-term innovation that could lead to efficient solutions of the future. Additionally, each firm producing and delivering energy had a unique production function. Thus, it is nearly impossible for the regulator to determine the correct price to perfectly satisfy Equation 1.1. Overall, the regulation of electricity markets has its economic and technical validity: it makes sense that there is some type of centralization of the US electric grid to promote technical efficiency. There could be strong economic and technical arguments supporting a regulated market, but they make false assumptions such as perfect information.

1.3.2 Electricity Restructuring in Chile

Chile was the first country to completely unbundle electricity generation, transmission, and distribution with the Electricity Act of 1982 (or Ley General de Servicios Electricos, or LGSE), which inspired similar movements across the world. The LGSE, in addition to its relevant amendments, regulates the rates and terms for electricity distribution(Acuña et al., 2017). The legislation mandates that the distribution companies must secure adequate power supply to all of their customers in a non-discriminatory manner. In order to do so, the distribution companies enter into long-term power purchase agreements, as described in Article 184 of the LGSE. The distribution tariffs consider the nodal price at the point of interconnection, in addition to the distribution aggregated value, which accounts for the "fixed costs per user, average losses of energy and capacity, standard costs of investment, maintenance and operation associated with distribution per unit of power supplied and the unique charge" (Mackenna et al., 2017).

Chile uses a centralized scheduling market based on audited costs, under the responsibility of the independent system operator, also known as a mandatory pool. Instead of using bids, the generators will inform the variable cost and expected availability to the system operator. Then, the system operator, known as the Independent Coordinator of the National Electricity System (CISEN) considers the network restrictions, congestion, variability in demand, hydrology, wind forecasts, and ultimately schedules a dispatch which is optimized to minimize the total operating cost of the system while maintaining the quality of service. The system operator also calculates the locational marginal price, which is used to settle contracts and provide data for future analysis. While there has always been a geographic and temporal component to electricity prices, the integration of variable energy sources and other intermittent energy sources further complicate the variability of energy prices.

There are centralized energy auctions for long-term contracts in order to ensure adequate energy supply, to promote competition in the market, and to reduce the risk associated with price volatility. While the contracts are intended to increase competition across distribution companies, the fact that the tenders are locked in long-term contracts with distribution companies actually "deter competition for a long period, excludes consumer choice and hinders the competition for additional services by retailers" (Faith Birol, 2018). While the distribution sector is intended to be competitive in theory, there are only two main distribution companies who deliver to the majority of the customers in Chile. The purchase of long-term contracts helps these large distribution companies maintain their market power. This impacts the customer directly, since the distribution companies play the role of both the distributor and retailer.

During the time of restructuring, some states and nations completely unbundled the roles of generation, transmission, distribution, and retailing. While the responsibilities of electricity distribution are technically liberated and left to private parties, Chile only has two main electricity distribution companies. One of which, Enel Distribución, also plays a large role in energy generation as well. Theoretically, competition among retailers should lead to more selection and variety in services and tariffs, that the customers could choose from. However, without a certain sense of customer awareness and comprehension, the competition among retailers would eventually be boiled down to competition between different advertising tactics, as seen with cellular phone providers.

1.3.3 Restructuring of the Electricity Industry in the United States

Under President Jimmy Carter's administration, the National Energy Act was passed in 1978 as a response to the oil crisis of 1973. The act included several important statutes, including the Public Utility Regulatory Policies Act (PURPA), the Energy Tax Act, National Energy Conservation Policy Act, Power Plant and Industrial Fuel Use Act, and Natural Gas Policy Act. PURPA was written with the intention of promoting energy conservation and inviting new energy producers to provide generation. PURPA also allowed an easier way for renewable energy technologies to supply electricity into the electric grid. Another important component of the act was to disassemble the traditional 'rate structures' used by utilities companies. Essentially, utility commissions were previously using a pricing mechanism that would decrease the cost of electricity as consumption increased. While this is a strong economic theory, it is counter-intuitive from an environmental perspective, and ultimately increased electricity demand.

More energy producers, IPPs, were welcome to join the electricity sector through the passing of PURPA. One important point, which still holds true today, is that utilities companies are required by law to purchase energy from IPPs at the market price. Thus, if an IPP produces energy in a more cost-efficient manner, then they can ultimately create a profit under this policy. In addition to this economic impact, PURPA also has technological effects on the grid. Some IPPs generate renewable energy, such as wind or solar energy, which could be quite unpredictable. However, the utility companies must meet the aggregated consumer's demands at every point of time in the day without resulting in a shortage or congestion. Therefore, the system operator must take into account the intermittency associated with the energy supplied by renewable IPPs. PURPA also helped spur an exponential increase in innovation in alternative energy technologies and allowed the industry to challenge the traditional vertically integrated utility company, essentially opening up the barrier to entry for IPPs. With this shift, people began to question whether a natural monopoly was the most technically and economically efficient strategy of the electricity industry.

Between the 1970's and 1990's, a number of industries which had been operated by a natural monopoly went through a series of deregulation and restructuring. Congress passed the Energy Policy Act of 1992 which encouraged energy efficiency, energy conservation of buildings, along with providing subsidies for clean energy. At this time, the end-user could not purchase electricity directly from IPPs, but this act allowed IPPS and utilities to connect alternative generation sources directly into the regional wholesale transmission system. This act helped further invite non-utility energy generators to enter the industry, and it is considered the foundation of electricity restructuring in the United States, by promising mandatory wholesale transmission. In 1995, FERC passed Order Number 888 which promotes wholesale competition through open access, ensures non-discriminatory transmission services by public utilities, and covers how public utilities will recover stranded assets during the restructuring.

In the late 1990's, various regions across the United States created Independent System Operators (ISOs) or Regional Transmission Organization (RTOs) and set up the wholesale electricity markets, day-ahead, ancillary, and capacity markets that we have today. The seven main electricity power markets across the United States include California ISO, Midcontinent ISO, Southwest Power Pool, Electric Reliability Council of Texas, Pennsylvania New Jersey Maryland (PJM), New York ISO, New England ISO. The ISO/RTOs operate the wholesale electricity markets and coordinate electricity transmission across the system. All of the ISO/RTOs are regulated by FERC, due to the interstate commerce, apart from ERCOT, which operates solely in Texas. The power pools have restructured in different ways, while some have completely competitive retail markets (ERCOT), and others retained a model similar to the natural monopoly of the utility.

While the restructuring encourages competition amongst generators, it remains fairly unopposed that the transmission and distribution system should remain regulated and centralized, though it would be helpful to have a policy instrument to incentivize upgrades to aging power systems infrastructure. This transition from vertically-integrated natural monopolies to the fragmentation of the market is known as vertical unbundling. With the increase of distributed generation technologies, this may lead to energy being consumed closer to where it is being produced.

There are several economic benefits of electricity restructuring. Ideally, one additional benefit of deregulated electricity market is having heterogeneous pricing schemes for different consumers. The increased competition among retailers should theoretically drive the price that the customer pays down to the marginal cost of electricity. The outcome of this expectation is further discussed in Section 1.4. While the utility companies were not incentivized to improve their efficiency with cost of service regulation, the increased competition should incentivize the generators to decrease the production cost of electricity generation through learning effects and other operating decisions. In the long run, the competition should lead to more efficient long-term investments, as well (Chris Knittel, n.d.), which will allow the market players to reduce the risk of volatile prices in the short-run. The long-term contracts also reduce the incentive for market players to exercise market power.

If implemented correctly, these claims should lead to an increase in economic welfare for both the producer and the consumer of the electricity market. This provides an exciting opportunity for retailers to experiment with retail services, design efficient pricing schemes, and strategize in order to meet various consumer demands, and to incorporate technical innovations, such as connected devices.

The role and responsibility of regulatory agencies will shift as the markets will inevitably shift, as well. In addition to their initial responsibilities, the regulating agencies are also responsible for making sure that everyone has access to reliable and affordable electricity. Additionally, the regulators must think about price stability through long term contracts. Finally, the regulating agents have allowed the customers the option of selecting a new retailer, rather than being assigned one (Eakin et al., 2002, 70). For context, the practice of forced reassignment was used with telephone companies, and did not receive positive feedback from the community.

However, there are some challenges associated with the electricity restructuring. For example, the information asymmetry between the generator and system operator still exists. If there are enough parties with market power, or if some generators choose to collude, this could still lead to economic inefficiencies. For example, the incumbent electricity providers must reassess the cost of their existing plants and recalculate how much demand they will be supplying with additional players on the market. This may include merges, acquisitions, the creation of new departments in existing companies, and the creation of new firms themselves. One of the largest concerns that arises with these transitions is the problem of “stranded assets." Some utilities were forced to shut down their power plants because they were no longer economically competitive after the restructuring. Thus, this would affect the long-term financing that the utility had planned for, leading to stranded assets, and a loss of social welfare overall. Other utilities were forced to sell their assets as a result of the change in regulation.

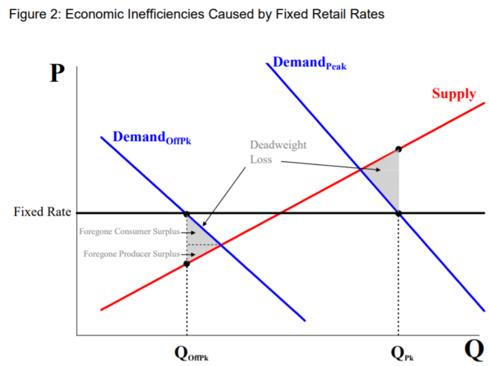


Figure 1-3: Economic Inefficiencies Caused by Fixed Retail Rates (Newell et al., 2009)

1.4 Tariff Design

The debate on electricity tariff design is as old as the industry itself (Greene, 1896). All over the world, electricity tariff design has a number of flaws which lead to a loss of total social welfare for end-consumers. In fact, academics and practitioners have been highlighting poorly designed electricity tariffs and recommending improvements for decades. However, the economic inefficiency due to misleading electricity tariffs are further exacerbated with distributed energy resources such as rooftop solar and electric vehicles.

Most residential customers have faced flat rate electricity pricing for decades, both before and after the restructuring of the electricity markets. Flat rates create economic inefficiencies, such as the over- and under- consumption of electricity during off and on peak periods respectively. Figure 1-3 highlights this economic inefficiency, known as the dead-weight loss (Newell et al., 2009). Dynamic pricing is an alternative that provides many benefits such as sending proper economic signals, decreasing the peak loads of the system, and improving long-term social welfare. The term *dynamic pricing* categorizes time-of-use pricing, critical peak pricing, peak time rebate, real time pricing (RTP), and several other variations that reach different levels of economic efficiency. Unlike time-of-use (TOU) rates, real-time pricing provides more specific incentives for customers to align their behavior with the marginal cost of electricity. This is primarily because TOU rates generalize over predefined blocks of time and the price difference is typically too small to encourage a change in consumer behavior (F.C.Schweppe et al., 1988). Despite this argument, TOU rates are more common for residential, commercial, and industrial customers than other approaches of dynamic pricing in the United States, due to their relative simplicity for consumer interpretability and utility implementation.

The issue of inefficient electricity pricing is certainly not a new problem. Prior to electricity market restructuring and before smart electricity meters with two-way 15-minute communications capabilities were used, James Bonbright described the importance of "time of day" and "time of season" energy rates which would eventually be more relevant with increasingly electrified houses (Bonbright, 1961). Even sixty years ago, Bonbright stressed the importance of promoting efficient resource use, interpretability of the tariffs, undue discrimination, and economic inefficiencies and unfairness associated with uniform rates (Bonbright, 1961). Several other economists related similar sentiments regarding the vulnerability of the consumer to the prices set by the utilities, which may be too high or too low to reach economic equilibrium (Kahn, 1988). Alfred Kahn was a strong advocate of peak-load pricing, which would reduce peak load, thus decreasing fixed costs for the system, and improving overall economic welfare in the long term (Joskow and Wolfram, 2012). Looking to global examples, Acton et. al wrote about best practices of time-varying energy charges, which reflect peak-load demand, that were implemented across Europe in the 1970's (Acton et al., 1978).

After the restructuring of the electricity markets, the conversation surrounding tariff design and time varying prices became more relevant and more prominent across the industry. In theory, competition among retailers should have invited more innovative and diverse set of tariffs offered to the customers. Unfortunately, apart from Texas, there has been limited competition among retailers in the United States. Thus, there has been less innovation among tariff design than necessary to keep up with changing market circumstances. For instance, while the fluctuation of wholesale electricity prices increased in recent years, retail prices have been adjusted gradually (Borenstein, 2005). This failure to target economic inefficiencies leads to higher risk of investment inadequacy when the retail rates do not properly reflect the wholesale electricity costs.

Practitioners highlighted the need to move towards more cost reflective electricity tariffs in order to promote economic efficiency, and help reduce greenhouse gas emissions through demand reduction. Proper price signals may save capital costs in the long-run. In particular, flat rate pricing bears the risk of providing worse incentives from a welfare perspective than time-varying pricing as demonstrated in pilots around the world (Faruqui, 2015).

Additionally, due to spatial diversity, there are some retail tariffs that may be more appropriate for certain geographical regions than others. For example, the marginal cost of electricity, consumer preferences, and demand curves vary across each utility's territory. Thus, it may not be appropriate to widely apply one tariff design across a large geographical region. In a similar vein, during the transition to RTP, the heterogeneity across customers can create inefficiencies and hurt the total social welfare. For example, if all of the customers of a community have RTP, then the allocation of costs are efficient. As highlighted by Borenstein, customers are not receiving equitable marginal surplus if some customers of the community have RTP, others have flat rate pricing, and other customers are still in the process of switching (Borenstein and Holland, 2005).

The question of economic efficiency of retail tariffs and sending proper economic signals is often exacerbated with the penetration of increased distributed energy resources. Fundamentally, the act of rate making will have to evolve with increased penetration of DER. For example, the rates were traditionally defined in a two-step process which involved calculating the total revenue that the utility must be reimbursed for its capital costs and services, with an additional "reasonable" rate of returned, followed by another step named rate design, where several parameters such as customer type, voltage level, and more come into play (Faruqui and George, 2006). However, this entire procedure will be disrupted and must be redesigned with additional customer-owned distributed energy resources and independent power producers.

Across the United States, Australia, Canada, and parts of the European Union, net metering is the incumbent policy for end-users who have distributed generation such as rooftop solar. Under net metering, the consumer is charged for the net amount of electricity drawn from the main grid, in kWh, after accounting for any surplus electricity injected back into the grid. While reducing this customer's electricity bill, this also places increased stress on the customers without distributed generation, who will be responsible for paying a larger share of the infrastructure costs. The net metering policies also do not send any signals to the customer based on the time of day to inject surplus energy back into the grid in order to balance the load, or reduce stress during high-peak periods. Finally, traditional business models do not provide an option for the household with distributed generation to sell surplus energy to its neighbors or promote local distribution.

Similarly, customers with electric vehicles can recharge their car with a meter at home, typically with no additional cost or installation (Charging Plug-In Electric Vehicles at Home 2019). Customers typically use the same electricity tariff to charge their electric vehicle as the one that supplies their electricity for the home. The utility gained from charging one's electric vehicle will be inherently different from the utility gained from other household appliances. Therefore, if the customer with an EV is withdrawing increased load during a peak demand period, and placing more congestion on the system, he is essentially placing more strain on the system. If the utility or distribution operator accrues additional network costs due to the increased load, the existing tariffs would allocate these network costs across all customers of the community, both those with and without EV's, creating a free rider problem.

Chapter 2

Role of a Distribution System Operator

Across the world, power grid infrastructure is aging, electricity demand is growing, and the urgent need to address climate change is motivating an ongoing energy transition (Nguyen et al., 2007). In order to adapt with this industry-wide transition, more innovative ways of operating distribution systems are being explored, such as with an agent that operates similar to an ISO but at a more granular level, known as a distribution system operator, or a DSO (Perez-Arriaga et al., 2016). A distribution system operator is a completely independent entity that could be responsible for optimizing DERs, promoting energy efficiency, demand response, distributed generation, incorporating electric mobility, microgrids, and energy storage. A DSO could be the appropriate agent to manage a traditional distribution system, and they could potentially operatoe similar to an urban microgrid.

The United States Department of Energy has defined a microgrid as a:

"*a group of interconnected loads and distributed energy resources within clearly defined electrical boundaries that acts as a single controllable entity with respect to the grid. A microgrid can connect and disconnect from the grid to enable it to operate in both grid-connected or island-mode*" (Ton et al., 2012).

The electricity generation of a microgrid could be supplied by any combination of multiple distributed energy resources, or by a single generator, depending on the location and nearby resources. As shown by the definition above, there is no predefined combination of Distributed Energy Resources (DER) or size requirements that a microgrid must meet in order to be qualified as an urban microgrid. However, the IEEE recommends that microgrids have a generating capacity of 10 MVA at a maximum. One of the main goals of traditional power systems operators is to balance the total electricity supply and the total electricity demand for its entire system at all times. The role of the distribution system operator is very similar: the DSO is responsible for balancing load and generation, monitoring frequency regulation and voltage control, along with most of the responsibilities of a power system operator, in addition to being responsible for the interface with the appropriate transmission system. There is generally one interconnection between the microgrid and the larger network; therefore the system operator of the transmission level views the microgrid as one individual node.

The microgrid could be connected to the larger electricity grid infrastructure, with or without the ability to go on island mode, or be completely detached from the main grid. The latter makes more sense for communities or commercial/industrial customers that are located in a more isolated location. Here, the main focus is on urban microgrids which are connected to the main infrastructure but may have the option to go on island mode for power quality and resiliency purposes during special circumstances. The term *urban microgrid* is sometimes referred to as community microgrid. The word *urban*, does not imply that is must be located in a city, but simply creates a distinction from rural microgrids, which are typically in isolated, underdeveloped locations without access to a grid.

Regardless of whether the community moves forward with a distribution system operator with or without an urban microgrid, the community energy provider would require a certain degree of community coordination and formal representation that could be carried out with a business model similar to an electricity cooperative. Electricity cooperatives have proved successful across the Midwest United States, and supply about 11% of the total kilowatt-hours delivered in the United States. These cooperatives are typically not-for-profit and act in the interest of the community members. However, many of the electric cooperatives are run and led by people on a voluntary basis without sufficient expertise in running a successful distribution system for many communities. Electricity cooperatives that would run and operate urban microgrids would most likely have a close relationship with the larger investor-owned utility. Therefore, it would be beneficial if a relationship between the urban microgrid operator and incumbent utility could form a relationship in the early pilot stages, if they are not the same party.

The following sections will introduce a number of advantages associated with a separate DSO, provide examples of federal and state research on urban microgrids, and list some of the associated economic challenges facing the implementation of a DSO.

2.1 Advantages of a Distribution System Operator

The legacy electricity infrastructure is quite dated, assumes unidirectional power flow, experiences losses along the transmission and distribution system, and requires upgrades to the infrastructure.

Instead of replacing the existing infrastructure with the same technology, there are multiple reasons why urban microgrids could prove to be a strong alternative. The advantages of an urban microgrids with a DSO are discussed in this section.

2.1.1 Resiliency

Water, electricity, and gas are often the first resources that must be recovered following a natural disaster, or supplied during dire circumstances. Thus, the distribution of these products must be reliable during times of high demand, unexpected weather circumstances, or product malfunction. For example, after Hurricane Sandy hit Northeast North America in November of 2012, more than 8 million customers were reported to have a power outage. By January of 2013, there were still thousands of customers without access to gas and electricity due to the storm (Nessen, 2013). After Hurricane Maria hit Puerto Rico in September of 2017, the average Puerto Rican household did not have access to electricity for approximately 85 days (Sweet, 2018). Not only did these power outages cost a lot to repair, but they also infringed a high economic cost to the city's productivity, such as shutting down the New York Stock Exchange for the first time in decades. Between 2003 and 2012, the cost of power outages due to extreme weather events was in the range of \$ 18 - \$ 33 Billion USD per year, including the cost of damaged power systems infrastructure, loss of productivity, and loss of output and wages (Hirscha et al., 2018).

With climate change, natural disasters are expected to become more severe and more frequent (Banwell et al., 2018). Instead of having a reactive approach, of rebuilding the same infrastructure after an extreme event, there must be a proactive approach in planning and rebuilding electricity distribution systems with more innovative and resilient systems.

2.1.2 Encourage the Integration of Distributed Energy Resources

A DSO would encourage and facilitate the increased integration of distributed energy resources across the system. There exists a lot of literature on the benefits provided by DER, which include the locational value, reliability and electricity services to the grid, economic incentives, employment opportunities, environmental benefits, and public health benefits (CleanCoalition, 2013; Burger, Jenkins, et al., 2019).

With increased DERs on the system, there is a challenge of operating the system with higher levels of intermittent energy and energy resources that are more difficult to predict. Thus, a distribution system operator could help address this challenge.

2.1.3 Reliability

While a power outage for residential customers may simply lead to an inconvenient evening, the cost of non-served energy is higher for customers that have very inelastic demand functions. For example, some commercial & industrial customers, including hospitals, military sites, financial facilities and research centers, have higher interruption costs and startup costs than other residential customers. Thus, these customers may have a higher willingness to pay for electricity service that can provide higher reliability. The Consortium for Electric Reliability Technology Solutions (CERTS), researchers are Lawrence Berkeley National Lab, and other research institutions have been doing rigorous research in designing the software such that a DSO could control distributed generation and ensure system-level reliability, which is one of the main drivers for implementing a DSO (Feng et al., 2018).

2.1.4 Impact on Infrastructure Costs

While energy discussions generally surround the investment in energy generation, Figure 2-1 displays the sheer magnitude of investments in distribution costs relative to other technologies of the power sector. The United States is currently in the process of replacing its electric grid as opposed to expanding it, as developing countries are in the process of doing. Given the asset lifetime and cost of replacing and upgrading existing transmission and distribution systems, efforts should be made to incorporate recent innovations where appropriate. Urban microgrids, along with other investments in updating distribution systems would have a great impact on infrastructure costs. Distributed energy resources could be strategically placed as to minimize the cost during peak demand periods through peak shaving. In addition to the impact on power systems infrastructure through peak shaving, urban microgrids could also replace or defer centralized network upgrade investments. The impact of distributed generation, and namely urban microgrids, on infrastructure costs varies greatly depending on the location, the respective utility's business model, size of the region, and feeder type. Literature on this topic has quantified the fiscal benefits of distributed generation deferring network upgrade investments range between 265 $\$/kVA$ up to 1200 $\$/kVA$ (Price, 2005; Gil et al., 2006).

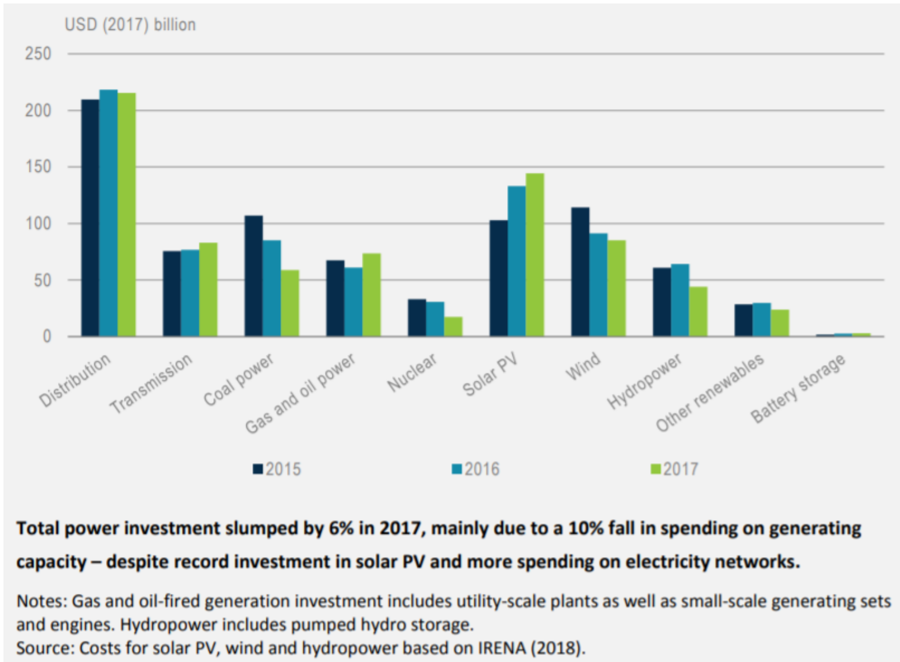


Figure 2-1: Global Investments in the Power Sector by Technology (Fatih Birol, 2018)

2.1.5 Decrease Transportation Losses

In the United States and European Union, the total losses along the transmission and distribution systems average roughly 7% of total power flow (Burger, Jenkins, et al., 2019) When current flows through transmission and distribution lines, there is inevitably electrical line losses (Beaty, 1998). The magnitude of the line loss depends on the amount of current flowing across the line and the resistance of the wire. With distributed generation, less electricity is being supplied from a centralized generator. Thus, less current is flowing across the transmission and distribution infrastructure, which therefore results in a reduction of losses. The literature supports that one of the strong benefits of local, distributed energy resources, is that it leads to line loss reduction (Méndez et al., 1993). The reduction of transportation loss varies depending on the system parameters and distance traveled. As expected, the further the centralized generator, the more benefits attributed to local distributed generation (Méndez et al., 1993). Although the amount of line loss reduction varies according to the type of generation, location, and system parameters, literature has calculated that DERs can reduce line losses in the range of 5 - 20 % (Burger, Jenkins, et al., 2019).

2.1.6 Bidirectional Power Flow

Previously, the centralized network operator used a top-down approach. Typically, the total generation was expected to meet the total demand, since there was less variable generation at the time. In order to dispatch future energy supplies, the network operators would use historic peaks and patterns. Traditionally, this pattern did not depend on active data or consumption habits or decision making at the end-user level. Now that we have bidirectional power flow, flexible load is able to alter its decision patterns based on consumer preferences and the energy supply across the day. However, if everybody has the ability to make this autonomous decision making, it would place a large burden on the centralized network operator to send the proper price signals and alter its dispatching according to each customer's heterogeneous preferences for their flexible demand. This topic is becoming increasingly important, because end-users will begin to have the power to make more decisions and use appliances that have flexible demand curves. The charging of electric vehicles provides a strong example, but more appliances will soon be dispersed among consumers. As opposed to expecting the centralized operator to account for this heterogeneity, or assuming that consumers have inelastic demand functions, a distribution system operator could help account for the bidirectional power flow and increasing amount of flexible loads.

2.1.7 Inefficient Electricity Tariffs

As aforementioned, inefficient electricity tariffs have persisted through the restructuring of electricity markets despite ample recommendations of alternative designs. Due to the lack of incentives, exacerbated inefficiencies associated with DERs, and lack of success with other policy measures, the implementation of a DSO would serve as an opportunity to move towards efficient electricity pricing. With access to a higher granularity of data, the DSO could implement a three-part tariff including a fixed charge, a demand charge, and an hourly DLMP. Since one tariff structure is not the best for all communities, the DSO could find the optimal tariff structure for the specific community it serves.

Given the fact that incumbent utilities are not moving towards more economically efficient tariffs at a fast rate, a strong case could be made that a distribution system operator could solve for the distributed LMP and could help incorporate more innovative, granular, and diverse electricity tariffs that are properly designed towards the specific community in which it will operate.

2.2 Regulatory Intervention regarding Microgrids

Each region's regulatory body must be prepared to set specific rules and standards for urban microgrids, including the interconnection into the main electric grid, allocate liability for the urban microgrid operation, establish rules to prevent stranded assets, and to set standards for the physical infrastructure. In fact, Japan is one of the first countries to clearly define technical guidelines and rules for the interconnection of urban microgrids into the larger system (Planasn et al., 2015).

In 2003, the Standard for Interconnecting Distributed Resources with Electric Power Systems (IEEE 1547) was established in order to standardize the interconnection of distributed resources into the electric power system. After eight years, IEEE 1547.4 was passed as the guidelines for distributed energy resources that could intentionally go on *island* mode from the traditional electrical power system. This standard included important aspects of voltage control and frequency regulation, and clearly states safety regulations for the interconnection of DER and microgrids into the traditional grid. Now, the industry is looking at 1547.4 to become the foundation for the standards of interconnection of urban microgrids into larger power systems. The following section discusses the government intervention of various geographies across the world in North and South America.

2.2.1 United States

The heightened need for resiliency and race to zero-carbon energy sources has driven efforts across the United States to research urban microgrids across the states. A lot of the federal and state support has come in the form of funding and encouraging microgrid R & D activities among the universities, national labs, and other research facilities. The research areas include improving the software and control of microgrids, thorough economic analyses, along with launching demonstration projects, further discussed in Section 2.4.

Within the United States Department of Energy, The Office of Electricity Delivery and Energy Reliability initiated the Renewable and Distributed Systems Integration (RDSI) program, which allocated $ 100 million USD, per project, to reach a 15% peak-load reduction (Feng et al., 2018).

In addition to the Department of Energy itself, the Department of Defense has its own motivations to advance research of microgrids for the purpose of supplying reliabile energy to its military bases in isolated locations. Thus, the DOE and DOD together started the Smart Power Infrastructure Demonstration for Energy Reliability and Security (SPIDERS) program in 2010. With SPIDERS, microgrid demonstrations have been developed on bases in Hawaii, Colorado, along with other locations. The success of these demonstrations has led to an increased adoption of the microgrid approach, such that almost all new military facilities now use them (Feng et al., 2018).

While the direct investments in R & D projects is one method of encouraging microgrids, the US federal government also provides tax incentives for the implementation of microgrid technologies (Feng et al., 2018).

The federal level has encouraged microgrid deployment through R & D funding and tax incentives. There have also been many state and local efforts towards implementing urban microgrids, especially in the 29 states that have Renewable Portfolio Standards (RPS) in place, by adding more pressure and support for R &D efforts, along with promoting innovative business models to incorporate DERs. For example, the state of New York State Energy Research Development Authority (NYSERDA) launched the New York Prize, which prides itself in being the first competition of its kind in the United States, that encourages innovation in the sapce of urban microgrids that must work in the case of a power outage or extreme weather event. In California, the California Energy Commission (CEC) allocated $45 million USD for microgrid demonstrations, which led to very successful projects across the state, as shown in Section 2.4.

In addition to the direct investments, some states have placed other financial investments through tax incentives, direct subsidies for specific technologies, rebate programs, and one specific program that encourages Property Assessed Clean Energy (PACE). The latter program, PACE, helps finance clean energy projects on private property. It has showed promising results in California, which has led the DOE and approximately 40 other states to pass a similar program.

While a lot of the government intervention remains on the R & D approach, there are still a lot of open questions regarding the regulation itself of urban micorgrids, such as whether they should be legally recognized as an IPP or an electricity distribution company. While most states in the US have not formally created a regulation specifically for urban microgrids, it is unclear as to whether the urban microgrid will legally be treated as its own utility or a DSO. One issue is that they cannot be properly categorized into anything defined by the existing regulation. Thus, new regulations must be updated to take this into account.

Although the regulations vary by state, the incumbent utility companies still have a lot of exclusive rights, such as serving to specific territories or over public roads, which they must follow, defined under the utility franchise rules (Valta et al., 2018). Being legally treated as a utility comes with a number of strict guidelines and financial responsibilities, which may deter small microgrids from trying to attain this status. However, this may limit its potential size and operation.

Another important question to ask is who will operate each urban microgrid. There has been research on different ownership models for privately owned microgrids that would benefit the customers and the electricity generators, but they typically do not benefit all of the relevant stakeholders, and thus either reach a standstill or are lobbied down by the utility companies (Faure et al., 2017). For example, there has been a proposal that the distribution company could still own all of the distribution infrastructure, and simply lease it to the microgrid owner, who may not be the main party operating the microgrid itself. Alternatively, the DSO itself could own and operate the microgrid. While the DSO model could allow for the utility to continue having a role with microgrid operations, the main criticisms are the high costs associated with the implementation. Another business model could be for a third-party entity to be financially responsible for owning the assets, while allowing the DSO to run and operate the microgrid. A third-party owned and operated microgrid could come in a number of different forms - it could look similar to an electricity cooperative, or be owned by a private energy company, or other financial parties. Finally, a hybrid model could allow where the DSO operates the microgrid, but the customers own the DERs. This type of business model may be attractive for customers who are already facing very high retail tariffs, and looking for alternative solutions. One of the greatest challenges associated with the hybrid model is the difficulty coordinating amongst different relevant parties (Valta et al., 2018). Similarly, there are many different combinations or types of community microgrids which would be suitable for some places and not for others. With these business models, it is important that the microgrid operator is somehow legally obliged to serve a certain quality of power, and there must be a contract set up so that they do not abandon the community, which would lead to a problem of stranded assets for the utility company. Thus, the business model for privately-owned microgrids must prevent a number of possible issues, while also being beneficial for the relevant stakeholders in the power sector, and seem feasible to the state regulators who would be allowing such business models. Ideally, the microgrid operator would bear the liability associated with providing reliable electricity to customers, but these guidelines have only been defined for public utility companies thus far.

In order to accelerate and standardize the process of building new microgrids, the OE placed significant efforts into creating standards for microgrids and microgrid controllers. The interconnection standards remain to be one of the largest hurdles for microgrids (Valta et al., 2018). A lack of standardization could lead to lower interoperability of different microgrids, and may ultimately lead to stranded assets in the long run. This makes the high investment a risky investment, which deters future microgrid implementations. Not only are the interconnection standards important, but also the cost of interconnection must be discussed between the main grid operator and the regulators.

2.2.2 Puerto Rico

Due to Hurricane Irma and Maria and the subsequent power outages and damage of electricity infrastructure, the development of microgrids in Puerto Rico has progressed rapidly out of necessity. After Hurricane Maria hit Puerto Rico in September of 2017, the average Puerto Rican household did not have access to electricity for approximately 85 days (Sweet, 2018), while the communities living in remote areas did not have electricity until December, approximately four months following the event. Following the natural disasters, many private parties were interested in helping rebuild and improve the electricity infrastructure using more modern technologies such as microgrids. Thus, the Puerto Rico electricity regulators responded with clear regulation and guidelines for the development of microgrids. The Puerto Rico Energy Commission (PREC) finalized the “Regulation on Microgrid Development of the Puerto Rico Energy Commision” in May of 2018 (“Regulation on Microgrid Development” 2018). The document sets clear rules and guidelines for short-term microgrid projects, along with long-term development of microgrids in the years to come, such as incorporating microgrids into the Integrated Resource Plan for Puerto Rico.

The regulation classifies and defines rules for personal microgrids, cooperative microgrids, and third-party microgrids, along with specific definitions for renewable microgrids and hybrid microgrids. PREC set clear guidelines for the ownership of microgrids, appropriate contracts required, the registration process, a standardized exit process, and sets guidelines for rate of service for all three types of microgrid.

PREC also asked the incumbent utility, Puerto Rico Electric Power Authority (PREPA) to set clear rules for interconnection standards for compatibility between microgrids with existing infrastructure. It asks all microgrids to meet the safety and performance standards defined by IEEE 1547 (of Energy, 2018). PREPA has defined a standardized process for independent microgrid operators to go through the entire process of completing the appropriate documentation, going through the safety tests, and reliability studies. Both PREC’s regulations and PREPA’s interconnection standards facilitate the process for microgrid development across Puerto Rico and help standardize the process.

2.2.3 Canada

Similar to the United States, there has been federal support in Canada for the research and development of urban microgrids across many of the provinces through Canada’s Department of Natural Resources. Over the past few decades, there has been approximately $38 million CAD of public funding towards microgrid demonstrations and pilots between 2003 and 2018 (Katiraei, 2018). The publicly funded microgrids are in collaboration with research institutions or private companies, with efforts to develop grid-connected urban microgrids in institutions, such as the University of Ontario Institute of Technology, mines, such as the Raglan Mine in Quebec, and urban microgrids connecting communities.

CanmetENERGY is the public research and technology organization within the Department of Natural Resources which has projects and research focused on smart grids and microgrids. A lot of their work is done at the Varennes Research Center in Quebec, which is made up of researchers, scientists, and experts in the field who manage projects and allocate federal funding for smart grids and other energy-related projects, while also collaborating with industry and academic institutions. where they are developing a Performance Assessment Tool for Remote Electrical Microgrids (PATREM). There are two other relevant publicly funded energy research laboratories in Devon, Alberta and Ottawa, Ontario.

In addition to the federal funding and research laboratories encouraging R & D of microgrids, the Department of Natural Resources has also organized and launched a Smart Grid Innovation Challenge to encourage creative and research in this space.

2.2.4 Chile

As discussed in Section 1.3.2, Chile has demonstrated remarkable reform in the electric power sector during the past 50 years. As one of the leaders of renewable energy in South America, Chile has installed a lot of renewable energy resources including solar, biomass, hydro, and geothermal energy. However, a lot of the renewable energy resources are built at a large scale at a location that is further away from the consumers, rather than a lot of local DERs such as rooftop solar.

The General Law for Electrical Services Article 147 (Artículo 147 Ley General de Servicios Eléctricos) allows for larger customers to purchase electricity directly from the generators rather than from the utility company. If a customer has a demand between 500 kW and 5000 kW, which are typically industrial or commercial customers, they have the option to sign a long-term contract directly with IPPs or local generators or purchase electricity from a retailer. In contrast, customers that have a demand above 5000 kW are considered a free client by law, and must negotiate their own contracts. This regulation is relevant because it could provide a pathway for urban microgrids to purchase electricity from the system operator or electricity markets, or local DERs, without going through a retailer. In theory, an urban microgrid could sign a PPA directly with an energy generator or IPP.

Though the Energy Commision in Chile does not explicitly have clear regulation for urban microgrids, the regulatory framework of Chile allows for multiple consumers to organize their own communal cooperative "behind the meter" as long as they are organized on private lands. In theory, multiple clients could form a sub-system and connect to the larger grid at one point of interconnection as long as they follow the appropriate safety and technical standards. In theory, the customers could organize their own tariff structure independently, and reduce the communal peak loads.

2.3 Additional Barriers for DSOs and Urban Microgrids

In addition to the regulatory challenges, there are several other barriers – primarily economic and social - that hinder the deployment of urban microgrids.

2.3.1 Pushback from Utilities

Many powerful, incumbent utility companies are concerned about the impact that urban microgrids could have on their revenues and business model overall. The management of more interconnection points to DERs and urban microgrids create more challenges for the utility company rather than practicing their current top-down approach.

One large concern is the impact of distributed energy resources on distribution systems with improper price signals, which could lead to the "Death Spiral Scenario," where utilities have to raise the rates to recover investment cost in infrastructure to handle intermittent generation from the expansion of renewable energy resources (Costello et al., 2014). The cost increases the incentive for customers to cut consumption either by increasing their efficiency or by installing on-site generation resources, creating a positive feedback loop. The poor customers cannot afford either of these options, thus leading to cross-subsidies where the lower income customers bear more of the burden. As stated by Professor Ignacio Perez-Arriaga, "there is no generally accepted approach to determine network charges for distributed generation and it can be considered as an open research topic" (Perez-Arriaga, 2016).

However, the industry proponents of urban microgrids do not have the motivation of replacing the utility. Instead, there could be a collaborative relationship between the existing utility and DSO, or microgrid operator. For example, there are already some large investor-owned-utilities, including ComEd (Illinois), Southern Company (Florida), Enel X (internationally) who are simulating virtual microgrids, studying pilots, and focusing more efforts on defining a sustainable business model for urban microgrids, as described in Section 2.4. The investments these utilities have placed in this field shows that they understand the oncoming shift in more distributed systems, and their interest in being a part of this solution rather than discouraging its advancement. A performance-based accountability for the utility would encourage them to upgrade their infrastructure efficiently.

2.3.2 Lack of Strong Consumer Incentive

From many consumers' perspective, electricity prices are so low that consumers are not incentivized to become actively engaged or lobby towards more progressive pricing schemes. One of the main problems is that the wealthy consumers who would be more likely to afford DERs or an urban microgrid are typically not the ones concerned about their electricity bill. In contrast, the low-income customers who are affected more by the tariff structure would face challenges to finance an urban microgrid without subsidies or financial support.

Overall, electricity regulation remains a deeply political issue – with regulators fearing backlash should they mandate dynamic or real-time pricing. From a political figure's perspective, it is a high risk for them to initiate a tax or change the tariff structure, which could potentially harm their political image.

For example, when the government initiated a gas tax in France in December of 2017, the citizens of France became actively engaged by protesting against the increase in gas prices, especially because it would have a greater impact on lower-to-middle income customers.

2.3.3 Economic Concerns

One of the main arguments against the development of urban microgrids or introducing a DSO is the high upfront costs. The concern is whether the benefits of urban microgrids warrant the high upfront cost of the urban microgrid infrastructure, which is significantly higher when the urban microgrid has the ability to disconnect from the main grid (Faure et al., 2017). For a community that has low electricity rates, few local distributed energy resources, and does not often have high peaks throughout the year, the cost of an urban microgrid may not make economic sense. Ultimately, the cost and benefits of an urban microgrid vary greatly with location, availability of local generation, and geometry of the system. Thus, each community or distribution grid must be studied on a case by case basis, rather than trying to make the argument that one system is always superior than the incumbent one.

However, the urban microgrids can provide strong economic benefits as well. As mentioned in Section 2.1.4, a lot of the distribution infrastructure in the United States is aging, and must be upgraded and replaced. Although it varies by location and system, new electricity distribution systems cost roughly $ 40,000 to $100,000 per mile (Hirscha et al., 2018). When assessing the upfront, fixed costs of urban microgrids itself, it could be seen as very high. But when compared to the existing infrastructure costs, the upfront costs of urban microgrids do not seem as infeasible. Since there is so much global spending on transmission & distribution costs, it might be better if the infrastructure is updated using more relevant and forward-looking technologies (Fatih Birol, 2018). Furthermore, community urban microgrids could actually be implemented using existing infrastructure, thus reducing the upfront costs (Hirscha et al., 2018). Similarly, the benefits of a DSO may outweight the high upfront costs, especially if it has the ability of implementing a DLMP or managing local generation in a more efficient way.

2.4 Current Implementations of Urban Microgrids in the United States

While some microgrid projects are still in the very early research stages, there are a number of pilot microgrids across the United States. About 34 % of the world's microgrid projects are located in the United States (Feng et al., 2018). In addition to the United States, there are demonstrations across the Asian Pacific, China, Japan, European Union, along with rural microgrids in developing nations.

While some of these projects are simply demonstrations of the feasibility, others are providing an alternative electricity system in isolated locations. Many of the organizations or institutions are those that need highly reliable electricity, and have the capital to spend upfront, such as military bases, universities, or other public institutions. These pilot projects display similar themes: an encouraging transition to coordinating low-carbon energy resources, improvements in control software, increased reliability for systems that need non-interruptible electricity supply, creating economic tools to analyze the financial feasibility, and starting to define standards for microgrids that could ideally be used universally (Feng et al., 2018).

2.4.1 California

California has demonstrated a number of urban microgrids across the state, with a few of them listed below. Most of the projects were implemented and studied by the Lawrence Berkeley National Laboratory, and primarily funded by the Department of Energy. The California Energy Commission has also recently granted funds specifically for projects involving urban microgrids and specifically focusing on how urban microgrids could benefit low-income communities.

Santa Rita Jail One of the earliest microgrid demonstrations, built in 2002, is the Alameda County Santa Rita Jail, which has the ability to go on island mode as needed. The tool developed at Lawrence Berkeley National Lab, DER-CAM, has played an instrumental role in the design and control of this microgrid. This project has collaborated with the main utility in the area, PG E, to reduce peak load by 15 % (Feng et al., 2018).

UC Irvine University of California, Irvine, has done advanced research in pilloting innovative smart grid technologies. It has also incorporated about 75 electric vehicles for the purpose of ride-sharing for the campus students. The campus microgrid has partnered with the local utility, Southern California Edison, to coordinate peak load shaving and demand response during times of congestion or high demand.

Borrego Springs Borrego Springs provides an interesting example, as the microgrid was built for an isolated community with a single transmission line connecting it to the main electric grid. While the DERs are owned by IPP's, the distribution assets are owned by the local utility, San Diego Gas Electric. This is a useful example displaying how private players and the incumbent utility company could agree on a cooperative business model which benefits both parties.

Other successful implementations of urban microgrids in California include the Chiquita Water Reclamation Plant, the Sierra Nevada Brewery, along with several vineyards, and other new projects in the planning stages.

2.4.2 Midwest

The Midwest has implemented about 60 urban microgrids as of 2018 across campuses, industrial customers, and for military purposes (Stark, 2018). After California, Illinois was ranked #2 across all of the states in terms of grid modernization. GridWise Alliance ranks the states based of of a Grid Modernization Index, which takes dynamic pricing, AMI penetration, progressive policies, and other factors into account (O'Boyle, 2017). Commonwealth Edison, a subsidiary of Exelon, (also known as ComEd) is one of the largest utility companies serving over four million customers in Illinois and has been actively experimenting and piloting grid modernization projects in order to provide energy services with greater reliability and from cleaner energy sources.

In addition to Illinois, Ohio has been rethinking how their electricity systems will evolve in the years to come. The Public Utilities Commission of Ohio (PUCO) has recently shifted their focus onto grid modernization of electricity distribution systems. PUCO, the four main utility companies, and relevant stakeholders came together to discuss pathways forward for grid modernization, including pilots of urban microgrids and facilitating the interconnection of urban microgrids with the larger grid.

Illinois Institute of Technology The Illinois Institute of Technology (IIT) is known to be one of the first efficient smart microgrid distribution systems in the world, which has rooftop solar, wind turbines, flow batteries, EV charging stations, and state-of-the-art smart control software. The microgrid has the ability to go on *island* mode within a short time period, and operates all of its distributed generation. The team at IIT is implementing and piloting state-of-the-art technologies and proving an important test case for similar projects. for example, it has built in the Intelligent Perfect Power System Controller (IPPSC) which acts as a building controller, has the ability to perform demand response, respond to disturbances within the system, and manage the storage systems (Feng et al., 2018).

Bronzeville, Chicago In February of 2018, the Illinois Commerce Commision approved ComEd's proposal to build a community microgrid in Bronzeville, Chicago IL. ComEd received $4 million from DOE to build a microgrid in Bronzevile, with additional funds from the Illinois General Assembly. The Bronzeville microgrid will be connected with IIT's in the efforts to create the "world's first microgrid cluster" with the ability to go on island mode. The motivation of the project is to encourage the integration of clean energy sources onto the system while maintaining reliable energy services during extreme weather events.

Shedd Aquarium The Shedd Aquarium is home for thousands of aquatic creatures, which requires consistent and reliable energy demand. With the goal of reducing their energy consumption by 50% by 2020, the Shedd Aquarium has implemented a microgrid that has the ability to go on island mode during extreme events. The microgrid has 265-kW solar system on its roof, 1 MW battery storage, with the controls and automation system operated by Schneider Electric (Stark, 2018).

Chapter 3

Facilitating Energy Transactions at the Distribution Level

Imagine a neighborhood where the households own a variety of DERs and have different consumption habits. For example, some households own rooftop solar, others own electric vehicles, some have a home storage unit, while other neighbors simply use the house as a vacation home. The different customers across the neighborhood will inevitably consume electricity at different times of the day and inject surplus energy at various magnitudes.

Under the current policies in the electricity industry, all of the customers will most likely pay the same rate if they have the same retailer and belong to the same tariff. Under net metering laws, the consumers that have surplus energy will reduce their electricity bill and will only be charged for the net load that they consume, after considering the amount of excess energy that they inject back into the grid.

If the neighborhood has a relatively more progressive rate structure, the retailer provide a tariff structure that charges the customers with "Real Time Pricing" which would charge the customer the hourly Locational Marginal Price (LMP). However, the LMP calculated by the system operator would be calculated for the transmission level, up to the nearest substation, but could not go down to the distribution level. In the presence of distribution congestion, a model that allows neighbors to trade surplus electricity with other neighbors, could encourage the use of local energy supplies while providing an opportunity to solve for the DLMP.

To illustrate the use-case of energy transactions further, the approach currently taken for industrial demand response allows a service providers to directly call industrial customers and ask the customer to curb their consumption accordingly. However, this same approach would be more difficult at the household level. It would be difficult to scale the same demand response procedures at a industrial level down to a residential level. As opposed to making physical phone calls, it would be more beneficial to communicate customer preferences and load data in a more efficient and progressive way. Ultimately, a decentralized approach is an alternative approach of engaging with the end user. Here, energy trading is further explored with the motivation of empowering end-users to participate in sustainable electric services while accounting for the true value of said services.

There are several different types of markets that allow for energy transactions, including a full peer-to-peer market, a community-based market, and a hybrid peer-to-peer market. While there are different types, there is no 'one size fits all' when it comes to the appropriate type for a specific community. Some communities may not even benefit from a peer-to-peer market. However, it is helpful to understand the different options.

- The *full peer-to-peer market* allows the agents of the community to directly communicate and negotiate with one another, without a centralized dispatcher. This allows each agent to take the opportunity to express their consumer preferences in order to reach the optimal outcome for themselves.

- The *community-based market* allows for energy transactions, with also having one party to oversee all the transactions and the point of interconnection with the rest of the system. Ideally, the community entering into a communal microgrid would share common characteristics. For example, they may be located nearby into a physical microgrid, or they may be a group of customers in New York City, interested in purchasing clean energy, and enter into a virtual microgrid that looks similar to virtual contracts. For example, there have been community members who enter into a community-based market to share the investments for energy storage and treat the stored energy as a communal good (Sousa et al., 2019). In this model, the shared energy storage is handled by a community manager rather than directly from one agent to the next. Thus, there is some type of transaction cost.
- Finally, the *hybrid energy transaction market* combines the two aforementioned types of markets. Thus, some of the agents belong to one subgroup of people, which is overseen by a community member. Within this subgroup, the agents communicate directly with one another. However, when the different subgroups communicate between one another through some type of centralized person, who would eventually communicate the outcome of the market transactions up to the system operator or the point of interconnection.

3.1 Motivation Behind Energy Transactions

While energy-trading markets would not be appropriate under all electricity systems or communities, it could provide a number of benefits when executed properly, which are explained below. For example, energy trading could provide more benefits for communities with connected devices and flexible load.

3.1.1 Distribution-Level Locational Marginal Price

In North America, South America, and Australia, the system operator calculates the Locational Marginal Price (LMP) for transmission nodes. Across several countries in Europe, including France, Germany, and Austria, they use zonal prices which are consistent across the entire country (Perez-Arriaga et al., 2016). However, the zonal price and the LMP across the transmission systems would be different from the prices at the nodes of the distribution level (Parhizi et al., 2016). A Distributed LMP, or DLMP, is a granular estimate of the short run marginal cost of electricity at a specific time and location of an electricity distribution system (Tabors, 2016). The Distributed LMP considers the marginal cost of energy, while accounting for DERs and physical limitations, such as congestion and network losses, of the distribution system. LMP's can vary across the system in the range between 5 - 10 %, when the system is approaching network constraints (Perez-Arriaga et al., 2016).

Currently, there are no power systems that calculate the price at the distribution level, known as a Distributed LMP, or DLMP, due to the complications associated with their computational feasibility. Energy economists claim that using a Distributed LMP instead of the LMP could help increase economic efficiency. Ideally, the DLMP would serve as a useful price signal to move towards socially optimal electricity consumption. As opposed to net metering policies, the DLMP could properly account for the true value / cost of energy injected by DER and encourage increased DER implementation.

Ultimately, it would be very computationally expensive to implement the same algorithm used at a transmission level to calculate DLMPS. Instead, the system needs a more innovative and feasible manner to manage millions of end-users. Peer-to-peer electricity trading helps find the proper amount of granularity, namely the DLMP. Not only will this quantify the short-run marginal cost of electricity with higher granularity, but it will also take the line losses into consideration. Computationally this makes more sense because using local information, local energy, and it is less data-intensive, as opposed to the alternative of expecting central operator to do it all.

3.1.2 Heterogeneous Demand Functions

The centralized algorithm used to dispatch electricity does not account for the demand elasticity of customers at the distribution level. Instead, it uses historic data and assumes that each customer has a purely inelastic, or vertical, demand function. Effectively, independent system operators assume that the customer will be willing to pay any price for electricity, because it is considered a necessity. However, customers do in fact have varying levels of demand elasticity for electricity. For example, there are some electricity services that must be completed within a certain time period, but do not need to be satisfied immediately. One of the most intuitive examples is the charging of electric vehicles. If a customer needs to drive to work by 7:00 AM, then hypothetically, it would not matter to the customer whether his/her electric vehicle is charged at midnight or 3:00 AM. Theoretically, this type of flexible load should be dispatched at the time when there is a high energy supply, such as wind energy, and the electricity is the cheapest. However, electricity demand functions have been estimated for decades. Many economists have defined various methods to quantify electricity demand for consumers. Economists have been trying to research and quantify the nuance of the consumer's demand for electricity since the 1970's. One example of this type of work, expanded upon by Dr. Daniel McFadden, is explained below.

Household Electricity Demand Curve Estimation

A Nobel Prize econometrician, Daniel McFadden, paved the way for econometric methods of modeling consumer's electricity demand. Daniel McFadden used econometric methods to model household electricity demand using several different data sets. In 1979, McFadden et. al used household electricity consumption data for 200 households collected over the course of one year in 15-minute interval (Hausman et al., 1979). This experiment was especially enlightening because of the high cost of advanced metering infrastructure during the time and the fact that it was still the very early stages of discussions surrounding real-time pricing or dynamic electricity pricing, further explored in **Chapter 1.4**.

In addition to analyzing the impact of time-of-day electricity pricing on household electricity consumption, the study also models the demand function for customers based on prices, weather, socioeconomic levels, and ownership of appliances. Using the demand function and indirect utility function, the study estimates the household's relative demand and absolute electricity demand for the respective time periods. Using this model, the study predicts hourly electricity demand on the household level.

The study assumed linear homogeneity, did not consider temporal effects, and did not have access to a data set with varying prices. While McFadden et. al's research in 1967 was very advanced for the time, it did face limitations due to the existing computer software and lack of access to appropriate data.

Modeling Residential Energy Demand The first step of modeling residential energy demand is assuming a customer's utility function (Cowing et al., 1984).

$$\underset{z,s}{max}\, U(z,s) \tag{3.1}$$

subject to

$$y = z + psh \tag{3.2}$$

where y resembles the household income, p is the price of energy, s is utilization of the energy usage, and h is the energy-utility ratio. Z represents all other household expenditures.

The indirect utility function can be derived from 3.1 and 3.2, to obtain the following:

$$u = V(y, ph) \tag{3.3}$$

where

$$V(y, \tilde{p}) = \underset{s}{max}\, U(y - \tilde{p}s, s) \tag{3.4}$$

The demand for energy can be found from the indirect utility function using Roy's Identity, expressed in 3.5

$$x = \frac{-\partial V(y, ph)/\partial p}{\partial V(y, ph)/\partial y} = sh \tag{3.5}$$

If the indirect utility function is of different form, the demand function will change, but Roy's Identity always holds.

The results from the Connecticut study using 1976 data led to a demand elasticity of -0.22 during morning hours (9-11 am), -0.13 during evening peak hours (5-7 pm), and -0.21 during intermediate periods (2-3 pm) (Hausman et al., 1979).

Another study used ordinary least squares of 1975 survey data to create demand functions for households in Washington (Dubin et al., 1984). These two examples demonstrate how the lack of sufficient electricity consumption data impeded a thorough analysis of household electricity usage on the appliance level. However, this restriction is of less importance given the decreasing price of advanced meters, the connectivity of household appliances, and more pilots of real-time-pricing.

Historically, a Lack of Quality Data

Daniel McFadden spent a lot of time breaking down the consumer's utility function for electricity consumption based off of appliance ownership, types of fuel, appliance efficiency, and fuel costs. He emphasized the lack of quality data on two fronts - for the econometrician and for the consumer itself.

In order to conduct the thorough analysis outlined by Daniel McFadden, it would require highly granular data set including appliance data, energy usage on the appliance level, and fuel costs per region (Cowing et al., 1984). In general, this type of data was not readily available in the 1980's, which is why he performed his analysis on survey data and alternative methods.

Additionally, McFadden outlines the difficulty for the consumer to obtain accurate and comprehensible information regarding their energy usage. "One question in the modeling of utilization is the quality of information on marginal energy costs available to the consumer, given the difficult of disentangling the effects of multiple end uses and stochastic components in energy consumption and the complexities of utility rate schedules" (Cowing et al., 1984). Unfortunately, the obscurity of the price of electricity for the consumer has not improved much over the past few decades.

Looking Ahead, Increased Intelligence and Data Management

In the past few decades, the cost of sensors and smart meters have decreased, while the amount of research and development of machine learning, artificial intelligence, and data analytics have improved. There has been a lot of speculation regarding how this heightened amount of connectivity and data management will impact various aspects of the energy industry. While many actors across the industry agree that the internet-of-things (IOT) and internet-connected devices (ICT) will impact the industry, there has been a lot of speculations and questions revolving what these impacts will look like. For example, industry reports predict that ICT will help improve resilience of the system, enable the utilities to use their resources more efficiently, and optimize power usage in general (Young et al., n.d.) in the journey towards an "intelligent grid."

In terms of electricity demand functions, there are many ways to use the data from connected devices which we could not take advantage of before. For example, at the household level, a home management system could predict the generation by DER and predict electricity demand across the data by learning from historic data. Each household could set its personal preferences of what time range the consumers would like their EV to be charged, or when they would like to charge their energy storage system rather than sell the surplus back to the grid.

Once the customer sets its personal preferences and customizes his/her home energy management system, the EMS can communicate the household's predicted generation and consumption habits to the distributed OPF algorithm in order to meet every customer's predetermined demand function and satisfy the thermal limits of the system. There are a number of ways in which ICT and IOT will help evaluate a consumer's electricity demand function. Energy trading platforms is just one example of how this increased level of information could benefit customers.

3.2 Literature Review on Alternative Energy Trading Approaches

Existing energy trading algorithms introduce a number of challenges regarding implementation or feasibility of being scaled up. Many approaches do not properly account for the infrastructure by modeling meshed systems, are not computationally efficient, do not include transaction costs or transmission charges, and end up being more similar to virtual contracts than something that emulates a physical system. Some of the existing energy transactions algorithms use linear programming, in addition to convex programming, stochastic optimization, genetic algorithm, particle swarm optimization, and game theory to minimize total energy costs (Alam et al., 2017).

In order to solve for the Distribution-Level LMP itself, there is no standard approach used across the literature. Some solve for the DLMP by using the Lagrangian from the AC OPF or DC OPF algorithm, used with existing power systems software (Meng et al., 2011; Y. Liu, J. Li, and L. Wu, 2018; Y. Liu, J. Li, L. Wu, and Q. Liu, 2016; T. Wu et al., 2005). Some researchers used similar optimization techniques to solve for the DLMP, but assumed that the agent solving for the DLMP has perfect information on the topology and cost functions at each of the nodes (Gerald T. Heydt et al., 2013; G. T. Heydt et al., 2012). Their approach was more similar to our "centralized with perfect information" case rather than a completely decentralized algorithm which only requires each agent to communicate with its immediate neighbors. Murphy et. al define an algorithm to solve for spot prices on radial distribution systems, which uses a similar method of communication between a node and its parent node (Murphy et al., 1994). Few of the papers solving for the DLMP suggest solutions to overcoming the computationally expensive top-down approach, account for the heterogeneous, elastic demand functions, or use a decentralized approach.

Another approach to solve for the DLMP is to formulate a method of dispatching electricity in a decentralized manner. Some of these algorithms aim to use augmented Lagrangian decomposition method where each node in the system optimizes for itself and then communicates its output to its neighbors, such as those explained by Kim et al., 1997 and R. Baldick et al., 1999. However, the earlier attempts did not properly account for the non-convexity question of OPF. Meanwhile, other approaches use dual decomposition to speed up the convergence time. The dual decomposition techniques include a combination of auxiliary variable method and alternating direction method of multiplier (ADMM)

(Lam, B. Zhang, and Tse, 2012; Lam, B. Zhang, Dominguez-Garcia, et al., 2012; Devane et al., 2013; N. Li et al., 2012; Dall'Anese et al., 2012; Kraning et al., 2013; Sun et al., 2013).

In order to account for the non-convexity and nonlinearity of the classic optimal power flow (OPF), there have been attempts to linearize the OPF for distribution systems, which also account for the loss factors of distribution (Yuan et al., 2018). Their results converge to those of the AC OPF, with minimal errors, but the algorithm does require complete information on the topology of the system. Thus, it does not calculate the DLMP in a decentralized manner. Similarly, Shaloudegi et. al propose alterantive method of solving for the DLMP by first optimizing for loss reduction using the standard LMP, then solving for the DLMP by accounting for the cost functions of each of the distributed generators on the distribution system (Shaloudegi et al., 2012).

In 2002, researchers proposed the Anthill Model, which emulates biological, complex adaptive system (CAS) by modeling the end nodes as ants that must communicate their costs and preferences through a larger, communal nest (Babaoglu et al., 1993). Another example, proposed by Wang et al., 2012 use a particle swarm optimization algorithm that can facilitate energy trading between buildings and the main electricity distributor. Their algorithm has a negotiation agent with the ability to learn and update according to the customer's behavior. There has been recent work using cloud computing and a fog-based approach to manage energy trading among residential customers. The fog server introduced by Khalid et al., 2017 also uses a neural network to predict future weather patterns and thus electricity generation from solar and wind resources.

There have been similar cost-minimizing algorithms that use a variety of different approaches. For example, several researchers use a heuristic approach based off of genetic algorithms to solve for the least-cost way of implementing real-time pricing for DC microgrids (C. Li et al., 2015). Their approach includes the total cost of power generation from the utility, energy storage, fuel cells, and the cost of line losses along transmission lines, along with demand response requirements imposed by the utility, but face a number of convergence issues such as the total time to complete all of the iterations becoming too long.

Another algorithm uses a combined solution to perform Demand Side Management (DSM) and peer-to-peer energy trading. Alam et al., 2017 describe a complex non-convex mixed integer non-linear programming (MINLP) problem, with the multiple objectives of cost minimization and ensuring that each customer is better off with the P2P than the model without the P2P. However, there are several flaws with forcing each customer to reduce their cost with the P2P model when compared with their existing costs. They are promising Pareto optimality, but in reality, the efficient price signals should be higher for some customers who must pay more for their higher consumption, when compared to their neighbors. As some customers transition from their existing tariff structure to the P2P model, some customers may pay more during this transition. This increase should not be viewed as an unfair cost distribution, but instead a price signal that they are willing to pay a higher amount than their neighbors, and in order to decrease their costs they must decrease or shift their demand. In addition to the multiple-objective optimization, they also capture the disutility for the customer when their electricity services are interrupted. Their optimization problem includes constraints based off of storage capacity, task duration, availability of renewable energy, uninterruptability constraints, power limits on the distribution lines, the maximum allowable delay, along with the Pareto Optimality constraints (Alam et al., 2017). Their approach schedules and shift loads, and also solves for the optimal quantity and price for each neighbor in the distribution system.

However, when running their approach on a case study with two households across eight time intervals, the MINLP setup for the problem introduces a concern with computation time. Their results showed that it may be difficult for their solver to run in a realistic timeframe, and their ongoing research has been on how to find the proper tradeoff between the optimal solution and computational efficient (Alam et al., 2017). There is a similar approach proposed by Zhang et. al which sketches out a four-layer architecture including the power grid layer, the ICT layer, control layer, and financial transactions. The four layers operate over multiple dimensions: the spatial features of the system, such as how the microgrid is set up, along with the temporal dimension. The name of the trading platform is known as "Eclecbay," which allows for transactions across buyers, sellers, and the Distribution System Operator (DSO). Their approach searches for the Nash equilibrium in every time step, while also obeyed the thermal constraints of the system.

Some researchers have been working on a platform named the Multi-Bilateral Economic Dispatch (MBED) which provides a transparent mechanism to clear the market while taking diverse customer preferences into account (Sorin et al., 2018). It uses a decentralized approach known as Relaxed Consensus & Innovation (RCI), which is very similar to a dual ascent method, to find the global optimum. However, the algorithm defined did not take the system parameters into account and displayed computational challenges when scaling up to a larger system.

One of the other algorithms that is very similar to the one outlined in **Chapter 4** was produced by researchers at Caltech. Also on a radial network, Qiuyu Peng and Steven Low proposed a distributed algorithm breaking down the Optimal Power Flow into multiple subproblems and then uses an approach known as alternating direction method of multiplier (ADMM). Their approach demonstrates positive qualities such as the ability to write the close form solution for each subproblem, which removes the need for multiple iterations for convergence. Additionally, their algorithm does not require the root note to communicate information amongst all of its nodes. Instead, each node only needs to communicate information to its neighboring nodes (Peng et al., 2014). However, the ADMM requires many iterations and is not feasible to scale up to the size of electricity power systems.

Overall, there are a number of algorithms aiming to find an alternative to the Optimal Power Flow (OPF) which will be useful with a heightened penetration of distributed energy resources and imperfect information for the centralized operator. However, some of algorithms introduced a number of challenges, such as their computational efficiency. If a proposed solution does not converge properly with less than 10 houses, then it would be difficult to scale the algorithm up. Furthermore, a lot of proposed algorithms fail to recognize the thermal constraints or physical parameters of the system. Thus, if the algorithm is simply minimizing cost without accounting for the spatial features of potential electricity trades, then the transactions are closer to a virtual contract rather than an electricity transaction. In contrast, our proposed algorithm considers and addresses these two drawbacks.

3.3 Proposed Energy Trading Platforms

Transactive Energy Business Model As one of the former governors of the California ISO, Ed Cazalet founded TeMix Inc and published a book regarding a Transactive Energy Market Platform. The Transactive Energy business model proposed by Ed Cazalet is intended to facilitate competition, provide an increased level of transparency and the standardization of electricity transactions across various types of agents. Essentially, the platform is a marketplace for consumers and producers to buy and sell electricity in a reliable manner, while ensuring reliable service. He compares it to Stubhub which sells baseball tickets and also charges an additional shipping fee. The two products that are bought and sold on the market include the energy itself and the “transport” of the power across T D lines (Cazalet et al., 2016).

Cazalet introduces both forward transactions and a spot market for operating decisions. Both of these markets are operated by the TE Platform. Customers can pay a ”subscription” for the use of transporting energy across T & D lines. Ideally, each household would have a home energy management system, which would allow the household appliances to communicate to the platform.

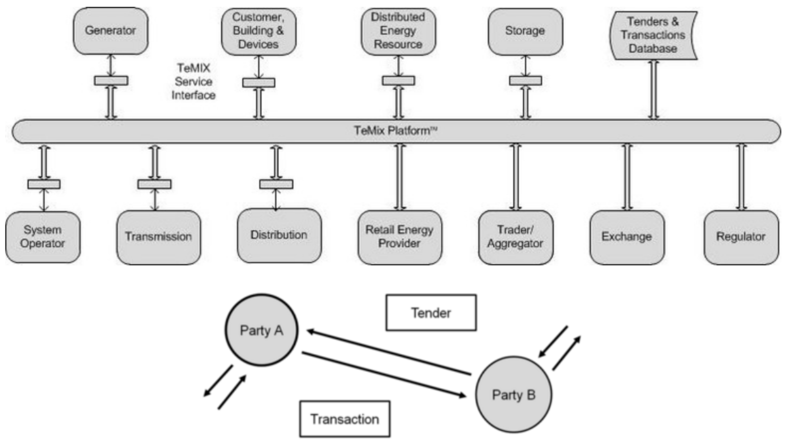


Figure 3-1: Potential Platform Market Structure Proposed by Ed Cazalet (Cazalet et al., 2016)

Approach Proposed by Tabors Caramanis Rudkevich (TCR) In light of New York's decarbonization efforts and need for increased power systems resiliency, highlighted by Superstorm Sandy, several New York authorities have initialized a state-wide effort named Reforming the Energy Vision (REV), which was created to transform New York state's energy policies and initiatives. In 2016, Tabors Caramanis Rudkevich, Inc (Tabors et al., 2016) wrote a white paper proposing ways in which the New York ISO could redesign their electricity markets to help reach their REV goals. The "White Paper on Developing Competitive Electricity Markets and Pricing Structures" describes a completely redesigned electricity market which is capable of handling real-time transactions on the distribution level. They proposed the introduction of a Distributed System Platform (DSP) which is responsible for grid operations, integrated system planning, and market operations. This model could be introduced while maintaining existing operations of incumbent distribution utilities. The Distribution System Operator would coordinate the selling and purchasing of real energy, reactive power, and reserves. In theory, their proposition would allow for the integration of more DER, helps maintain the appropriate voltage levels, allows consumers to transact directly with one another with transparency, minimize transaction costs, and financially clear the forward market.

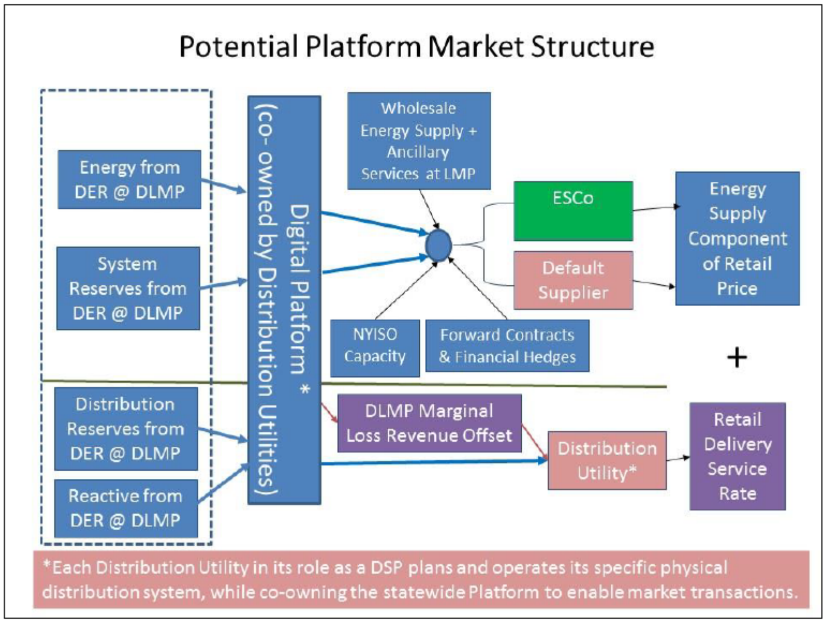


Figure 3-2: Potential Platform Market Structure Proposed by TCR to NYSERDA (Tabors et al., 2016)

Tabors, Caramanis, and Rudkevich clearly outline the design of the market platform, several business models that could be implemented, and potential licensing and ownership models. In order to bring this Distributed System Platform into fruition, there would need to be a lot of coordination between the New York Independent System Operator, distribution utilities, state regulators, and the development of a platform sponsor. More importantly, the success of the model depends upon the quantity and commitment of a variety of market participants – which include DER owners, distributed generation developers, larger generators, bulk power resources, and distribution utilities or ESCOs. Even if the New York State Public Service Commission, supports the proposed solution, the implementation of this model requires a lot of time, commitment, upfront cost, which may discourage some of the relevant stakeholders and be further delayed due to regulatory capture.

However, there are some key aspects of their proposed model that could be incorporated in other business models. For example, TCR emphasize the importance and success in the New York ISO of "getting the prices right" and saw it fit to draw from the expertise of the ISO to define and calculate the Distribution-Level Locational Marginal Price (DLMP), which can quantify the value of DER products. This tool should be considered when designing efficient electricity tariffs in the future (Tabors et al., 2016).

3.4 Markets Allowing for Energy Transactions: Implementations in Practice

There are several implementations of peer-to-peer marketplaces all over the world - from the United Kingdom to New York City to Australia. Several of them and their unique characteristics are discussed below.

Power Ledger

Power Ledger, based in Australia, is one of the largest players in the energy trading field. They aim to provide customers with an opportunity to gain the true value of the surplus energy from DER and to operate the transactions in a trusted trading platform. They believe that this peer-to-peer market requires a centralized player to oversee the transactions and ensure trust. The Power Ledger Platform uses "Smart contracts" with blockchain technology to enable these energy transactions with trust and transparency (Martin, 2018). They introduce one market for P2P trading, which communicates with an energy utility company that would buy energy from the larger wholesale market. Since 2016, Power Ledger has run some pilots in Western Australia, in communities of town houses or shopping plazas. They have expanded their projects to Northwestern University, Chang Mai University, and in a smart city pilot in Japan, along with other locations.

LO3 Energy

One of the most well-known examples of a P2P market is the Brooklyn microgrid experiment, where a full microgrid market was developed and encouraged customers to form bilateral trade for the purpose of charging their EVs with surplus energy from other agents (Sousa et al., 2019).

Piclo

Piclo is an online peer-to-peer electricity trading platform operated in the United Kingdom by Open Utility. The initial pilot was funded by the United Kingdom Energy and Climate Change Department and a venture capital group (Parka et al., 2017). Open Utility only provides renewable energy, and is trying to facilitate energy trading of clean energy sources with electricity consumers that have high demand. They balance the market transactions in 30-minute intervals with the cost of power generation, load data from the customers' meters, and individual customer preferences. For example, a customer can prioritize specific electricity generators over others based off of location or their personal preferences.

SonnenCommunity

SonnenCommunity is group of people who have the energy storage service, sonnenBatterie, in Germany, with the ability to share excess energy with their neighbors or peers. One unique attribute is that they combine both the photovoltaics and storage services together (C. Zhang, J. Wu, Long, et al., 2017), thus, any surplus energy is stored for the communal use in future time periods rather than sold back to the main utility.

Vandebron

Vandebron operates in the Netherlands and emphasizes the opportunity for customers to have the ability to purchase electricity directly from IPPs (Parka et al., 2017). For example, farmers in the Netherlands can purchase electricity directly from wind turbine operators. This model is more focused on the ability for customers to purchase directly from distributed generators, rather than the peer-to-peer aspect.

Electron

Electron also operates in the United Kingdom, and uses blockchain to ensure direct, decentralized, and secure transactions between consumers and producers. Electron has a flexible trading platform for peer-to-peer transactions in the short-term, they also have the ability to set up long term contracts, or collectively invest in DERs. They advocate that their use of blockchain technology will make electricity billing more efficient in the long run.

Chapter 4

Dispatching at the Distribution Level

As aforementioned, there are advantages in having a Distribution System Operator (DSO) operate at a more granular level than a traditional Independent System Operator (ISO) or Regional Transmission Organization (RTO). However, the existing literature displays difficulties in implementing an alternative algorithm to dispatch electricity at the distribution level and converge to the centralized algorithm while also displaying computational feasibility. The traditional Optimal Power Flow (OPF) algorithm used in the United States and the proposed alternative approach are described in this chapter, followed by several proof-of-concept examples.

4.1 Optimal Power Flow

Optimal power flow (OPF), a non-linear optimization problem is one of the most complicated and important problems posed in power systems modeling. Physically, the electricity dispatch must respect the nonlinear constraints of the system including the thermal flow limits across the lines and the operating limits imposed by the generating units. The main motivation of OPF is to minimize the total operating cost while ensuring that the supply meets forecasted demand and the electricity dispatch adheres to the power flow constraints across the system. Thus, OPF is a combination of centralized economic dispatch and power systems analysis, which must be solved concurrently. Since it is a non-convex, non-linear problem, system operators use an approximation to reach an acceptable solution (O'Neill et al., 2013). System operators today use security-constrained economic dispatch and security-constrained unit commitment during normal conditions when there is no congestion. The common approach linearizes the problem, uses a proxy for the line flow limits, and makes other simplifications, which may lead to a sub-optimal solution. It has been argued that nonlinear solvers do not find the global optimum, are not robust, and are not converging quickly enough (O'Neill et al., 2013). Over the past century, the OPF has been solved in a number of different ways - electricians were said to have solved it by hand in the 1930's and there was a time when the computation time was close to 10 minutes (Kirchmayer, 1958). In present times, the ISO/RTO can solve the OPF in seconds. Researchers have used the Gauss-Seidel method, the Newton-Rhapson method to solve the OPF, and Monte Carlo methods to quantify the uncertainty associated with the OPF (O'Neill et al., 2013). The most common approach uses classic Lagrangian methods, as proposed by Carpentier in 1960 (Carpentier, 1962). Overall, the problem itself poses a number of challenges as it is prone to ill-conditioning, is a fundamentally conservative problem, and often has problems converging (O'Neill et al., 2013).

OPF Algorithm

The incumbent centralized OPF algorithm, known as the most efficient way to dispatch electricity by a central operator with perfect information, is as described:

$$\min_{\mathrm{x}} \sum_{i \in \mathcal{N}} C_i(x_i) \tag{4.1a}$$

$$s.t. \;\; \mathrm{F}^{\mathrm{min}} \leq \mathrm{Dx} \leq \mathrm{F}^{\mathrm{max}} \tag{4.1b}$$

$$\mathrm{x}^{\mathrm{min}} \leq \mathrm{x} \leq \mathrm{x}^{\mathrm{max}} \tag{4.1c}$$

$$\sum_{n=1}^{N} \mathrm{x_i} = 0 \tag{4.1d}$$

Here, x is the vector of real power injection or real power load, $x_i \forall i \in \mathcal{N}$ of all nodes in the networks. Positive $\mathrm{x_i}$ indicates power injection, while negative $\mathrm{x_i}$ indicates power consumption. The cost function $C_i(x_i)$ of each agent is assumed to be convex. The Distribution Factor matrix $D \in \mathrm{R}^{m \times n}$ maps the node injections to line flows in the network, where m, n respectively is the cardinality of edges and nodes in the system. This mapping is based on the physical conservation laws at each node and/or the constitutive relations of the voltages and currents based on the network impedance values. The real power flows are found by applying the matrix operator D on to the vector of injections, which must stay within the real power proxy line limits $\mathrm{F}^{\mathrm{min}}$ and $\mathrm{F}^{\mathrm{max}}$, which are dictated by the thermal limitations of the wires. The third constraint is essentially Kirchoff's Current Laws, which require all of the net power injections and load to equal zero.

Overall, the problem is to be solved such that the limits on states of the agents and the flows are obeyed. The problem can be solved by the centralized entity if the details of each and every agent are known. The network structure also needs to be known in entirety.

Limitations Associated with OPF

The incumbent method, the optimal power flow (OPF) reaches economic equilibrium assuming perfect information under the static case. However, the information asymmetry between the operator and consumers will be further exacerbated with increased DER penetration, and it is not feasible for the centralized operator to account for so many distributed resources at the household level. Currently, aggregators collect information from DERs, but this may not be the most efficient way moving forward.

It is also expected that the variable generation from renewable energy resources will place more strain on the system operator which uses a model that was designed for a smaller number of more predictable, scheduled energy generation (Joskow, 2019). In contrast, the intermittent renewable energy sources are difficult to predict and control. This additional uncertainty has a negative impact on the performance of the system operator.

Additionally, short term generation dispatching assumes that electricity demand is purely inelastic, and these loads are predicted using historic data. However, this does not take into account heterogeneous customer preferences, or the diversity of demand elasticity for different products. Currently, there is no streamlined process to share information from household end products to the centralized market operator. Yet, this information is very valuable to predict future generation and demand curves and shifting loads accordingly.

4.2 Decentralized Economic Dispatch

A potential solution to overcome the information asymmetry and heterogeneous demand functions could be a higher degree of decentralization in system operation. Conducted on a more local level, the operator would have access to the detailed information and perform the same economic dispatch model to find the optimal prices while also satisfying the physical constraints of the system. Here, we will explain the decentralized algorithm which converges to the same solution as the centralized OPF with perfect information.

Recursive Distributed Algorithm

Consider a radial distribution network modeled as a radial graph denoted by $(\mathcal{N}, \mathcal{E})$, where $\mathcal{N} = \{1, 2, \ldots i\}$ is the set of nodes and $\mathcal{E} \subseteq \mathcal{N} \times \mathcal{N}$ is a set of ordered pair of nodes (i, j) which means that node i is physically or digitally connected to node j and thus can access information from agent j. The nodes of the graph belong to different layers $l \in \mathcal{L}$ where the set $\mathcal{L} = \{1, 2, \ldots l\}$ represents the depth of the tree. For example, the 8-node example displayed in Figure 4-3 has 3 Layers. Furthermore, every node $i \in \mathcal{N}$ has an associated parent node $p \in \mathcal{P}_i$ which represents the node above node i in a tree-like radial structure. Similarly, each node i is associated with a set of children nodes $c \in \mathcal{C}_i$, which are all of the nodes directly below node i (Jaddivada et al., 2019). Some nodes have multiple children nodes, while others have none.

The algorithm involves two paths for information exchange, referred to as the *forward* and *backward* sweep. The objective of the algorithm is to minimize the sum of cost functions of each agent while obeying the network constraints.

The general node in the middle of the radial system has a parent node, p_i, where $\{p \in \mathcal{P}_i\}$, and child node, c_i, where $\{c \in \mathcal{C}_i\}$. Y_{pi} represents the power flow from the parent node to the node i. Y_{ic} represents the power flow from node i to the child node, as displayed in Figure 4-1. Due to the assumption of radial graphs, the cardinality holds true such that $|\mathcal{P}_i| = 1 \ \forall i \in \mathcal{N}$.

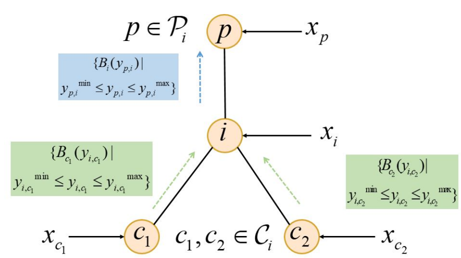


Figure 4-1: Information exchange during the phase of forward sweep: The communicated information from the children nodes is shown in green and the one computed to be sent to the parent node is shown in blue (Jaddivada et al., 2019).

In the forward sweep, information is communicated bottom-up by the nodes. Here, the nodes communicate their preferences through a *bid function* corresponding to the needs of itself and its children nodes. These functions abstract the cost function,or benefit function, of the aggregate of a specific node, together with its children nodes, by accounting for the network constraints. Once the bid functions reach the root node, the bid functions of children nodes are optimized for by the parent nodes. This proceeds sequentially in a top-down manner from the root node to the leaf nodes, and is referred to as backward sweep.

Forward sweep algorithm The information exchange framework bottom-up for the single node is shown in the Fig. 4-1. Given the information of the bids from its children nodes, the node i solves the problem posed in Equation (4.2) by assuming certain parent branch injections $\hat{y}_{pi}$ subject to branch flow and power balance at the node. This can be represented as:

$$\Pi^{\mathrm{i,Forward}} : \min_{x_i, y_{ic}} \; C_i(x_i) + \sum_{c \in \mathscr{C}_i} B_c(y_{ic}) \tag{4.2a}$$

$$s.t. \;\; x_i + \hat{y}_{pi} = \sum_{c \in \mathscr{C}_i} y_{ic} \qquad (\lambda_i) \tag{4.2b}$$

$$x_i^{\min} \leq x_i \leq x_i^{\max} \tag{4.2c}$$

$$F_{ic}^{\min} \leq y_{ic} \leq F_{pi}^{\max} \tag{4.2d}$$

Here C_i is the cost function, or benefit function, of agent i as in the centralized problem, defined in Equation (4.1). The children bid functions $B_c(y_{ic})$ abstract the bid functions of all its grand-children i.e. $\forall j \in \mathscr{C}_{C_i}$. Recursively, this abstracts the information of all the nodes reachable from the node i. The bid function to be communicated to the parent node is found by solving for the Lagrangian, λ_i, for three different expected injections from the parent nodes, $(\lambda_i, \hat{y}_{pi}), (\lambda_i^+, (1+\epsilon)\hat{y}_{pi}), (\lambda_i, (1-\epsilon)\hat{y}_{pi})$, where ϵ is chosen to be a small number such as 0.001. The incremental cost λ and parent branch injections y_{pi} are interpolated to find the slope and intercept values a_i, b_i, respectively, of the three points. The slope and intercept are then utilized to create a bid function of the form $B_i(y_{pi}) = \frac{a_i}{2} y_{pi}^2 + b_i y_{pi}$. While these functions are created, the limits on the desired parent power injections are concurrently updated, as follows:

$$y_{pi}^{\min} = \max\left(F_{pi}^{min}, \sum_{c \in \mathscr{C}_i} y_{ic}^{\min} + x_i^{\min}\right) \tag{4.3a}$$

$$y_{pi}^{\max} = \min\left(F_{pi}^{max}, \sum_{c \in \mathscr{C}_i} y_{ic}^{\min} + x_i^{\max}\right) \tag{4.3b}$$

These bid functions are sequentially communicated from layers N to 1 thus aggregating the information of the children nodes. Once the root node is reached, the downward sweep of the algorithm is initiated as described in the following section.

Backward sweep algorithm at each peer Here, the information from the bids from all the children and the available injections at the parent node are utilized to find the node injections x_i and the children branch flows y_{ic} by solving the problem in Equation (4.4):

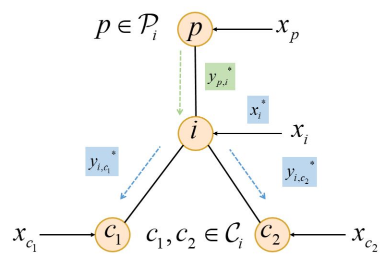


Figure 4-2: Information exchange during the phase of Backward sweep: The information from the parent node is shown in green and the information computed at node i, intended to be sent to children nodes is shown in blue

$$\Pi^{\text{i, Backward}} : \min_{x_i, y_{pi}, y_{ic}} \; C_i(x_i) + \sum_{x \in \mathscr{C}_i} B_c(y_{ic}) + \lambda_{pi} y_{pi} \tag{4.4a}$$

$$s.t. \;\; x_i + y_{pi} - \sum_{x \in \mathscr{C}_i} y_{ic} = 0 \tag{4.4b}$$

$$y*_{pi} \leq y_{pi} \leq y*_{pi} \tag{4.4c}$$

$$x_i^{\text{min}} \leq x_i \leq x_i^{\text{max}} \tag{4.4d}$$

$$F_{pi}^{min} \leq D_{ii} x_i + D_{ip} x_p \leq F_{pi}^{max} \tag{4.4e}$$

Here, DF_{ij} correspond to the element in i^{th} row and j^{th} column of the Distribution Factor matrix DF introduced in Equation (4.1). The Lagrangian, λ_{pi}, is the nodal price communicated from the parent node to its children node, such that the price of energy is passed down the radial structure. The information needed for the backward sweep is shown in Fig. 4-2.

4.3 8-Bus Proof of Concept

Imagine that the eight-node network shown in Fig. 4-3 is comprised of eight houses with diverse cost functions, as listed in Table 4.1. Some customers may have distributed generation such as rooftop solar, while other houses have flexible load such as electric vehicles. Thus, the cost functions, C_i, can capture the diverse customer demand profiles for each agent. In this proof-of-concept example, the cost functions are fictitious, though they are further explored in a later section. Along with the cost

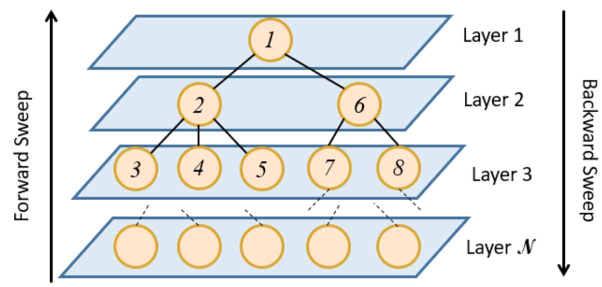


Figure 4-3: Eight-Node Network

functions, the system parameters such as minimum and maximum power injection at each node, and the maximum power flow across each line are also listed in Table 4.1. The V_{min} for each node is 0.9, the V_{max} for each node is 1.1. The minimum flow along each line is effectively the opposite of the maximum flow. In other words, $F_{min} = -F_{max}$. The initial power injections for each node is listed in the same table.

The distribution factor matrix, *DF*, relates the power injections at each nodes to the power line flow sensitivities of the connecting branch (Ilic and Zaborszky, 2000). *DF* are computed using network parameters and the system topology (Ilic, Xie, et al., 2013). The flows, F_{ij} are found by applying the matrix operator DF on to the vector of injections, which results in the flow along the respective branch. The distribution factor used in this example is contrived from the aforementioned system parameters, given by:

$$DF = \begin{bmatrix} 0.5 & -0.5 & -0.5 & -0.5 & -0.5 & 0.5 & 0.5 & 0.5 \\ 0.125 & 0.125 & -0.875 & 0.125 & 0.125 & 0.125 & 0.125 & 0.125 \\ 0.125 & 0.125 & 0.125 & -0.875 & 0.125 & 0.125 & 0.125 & 0.125 \\ 0.125 & 0.125 & 0.125 & 0.125 & -0.8750.125 & 0.125 & 0.125 & \\ 0.375 & 0.375 & 0.375 & 0.375 & 0.375 & -0.625 & -0.625 & -0.625 \\ 0.125 & 0.125 & 0.125 & 0.125 & 0.125 & 0.125 & -0.875 & 0.125 \\ 0.125 & 0.125 & 0.125 & 0.125 & 0.125 & 0.125 & 0.125 & -0.875 \end{bmatrix} \tag{4.5}$$

On the Forward Sweep, the bid functions for the Leaf Nodes, or nodes on Tier 3, are calculated by perturbing the flow limits of the branch between the leaf Node and its parent node. After perturbing the flow limits by 5%, a bid function is estimated for each of the Leaf Nodes, and the flow limits for each of the nodes are updated accordingly, as defined in Equation 4.3 and displayed in Table 4.2. Thus, the

Bus #	Cost Function $C(P_i) = aP_i^2 + bP_i + c$ a	b	c	P_0 (kW)	P_{min} (kW)	P_{max} (kW)	F_{max} (kW)
1	0.001	5	0	2	0.25	5	3.7
2	0.001	0.5	0	1	0.25	4	3.7
3	0.001	2	0	-2	-5	2	3.7
4	0.001	1	0	-.25	-4	2	3.7
5	0.001	4	1	-1	-4	2	3.7
6	0.001	2	0.5	-.75	-4	2	3.7
7	0.001	6	0.5	-1	-4	3	3.7
8	0.001	3	0.5	-1	-4	3	3.7

Table 4.1: Cost Functions of Eight Buses and System Parameters

process is repeated for the nodes on the middle tiers, all the way up to the Root Node, Node 1.

Flow	Bid Func $(y_{ij}) = \frac{a}{2}y_{ij}^2 + by_{ij}$ a	b	$y_{ij,min}$ (kW)	$y_{ij,max}$ (kW)
y_{12}	0	- 1.996	-3.7	3.7
y_{23}	0	-1.996	-2	3.7
y_{24}	0	-0.999	-2	3.7
y_{25}	0	-3.998	-2	3.7
y_{16}	0	-2.998	-3.75	3.7
y_{67}	0	-5.998	-3	3.7
y_{68}	0	-2.998	-3	3.7

Table 4.2: Bid Functions and Flow Constraints of Eight Buses

It makes intuitive sense that all of the bid functions have a negative coefficient. Instead of the cost of producing, the bid function captures the willingness to pay for power flowing through the respective branch to that node, and the negative sign implies that the customer is paying rather than receiving money. As shown in Table 4.2, Bus 5 and Bus 7 have a higher coefficient on the bid function, and thus a higher willingness to pay, which is consistent with the final power injections, because those two nodes consumed electricity up until the flow limits permitted, -3.7. This result is important, because it shows that the algorithm converges even with congestion, or when the flows approach hard flow limits.

After the bid function for all of the children nodes are estimated recursively, the Backward Sweep begins. Using the cost function of each node, the flow limitations from its parent node, and the bid functions of the node's children, the algorithm solves for the power injection, P_i, for each node and the power flow to its respective children. Thus, the Downward Sweep iterates from the parent, through the middle nodes, down towards the Leaf Nodes.

The output of the centralized OPF is displayed in Table 4.3. Ultimately, both the centralized OPF and the nested aggregation algorithm reached the same output, stated in Table 4.3. A positive P implies that the node injects power into the network, while a negative P means that the node consumes power from the network. Thus, the customers at Bus 5, Bus 7, and Bus 8 are consumers, while the other eight buses are producers within the system. X_i, or P_i in this case, signifies the power injection at that node. If the power injection is positive, the node, or house is injected power into the network. If the power injection is negative, the customer is withdrawing power from its neighbors.

Bus #	1	2	3	4	5	6	7	8
P_c^* P_{P2P}^*	0.25 0.25	4.0 4.0	1.15 1.15	2 2	-3.7 -3.7	2 2	-3.7 -3.7	-2 -2

Table 4.3: Optimal Power Injections of an 8-Bus System

4.4 Implementation on the System in Flores

In order to further display the benefits of the distributed OPF algorithm, another example is implemented on a radial 46-Bus electricity distribution system using real-world data from an island in the Azores Archipelago. The island has about 4,000 people and has an area of roughly 143 km^2 (Ilic, Xie, et al., 2013). The system is located on a remote island, Flores, in the middle of the Atlantic Ocean. However, the results are generalizable to electricity systems in urban contexts and in other geographical locations. The island provides a useful example of a radial electricity system in an isolated location, as opposed to a subsection of a larger electricity system, which may have unknown interrelated effects. Currently, the island imports expensive fossil fuels as its main energy source. However, Flores has the proper climate for a variety of renewable energy resources, such as wind turbines, solar energy, hydropower, and geothermal energy. The simulations presented here will use the actual system topography and vary the levels of DERs and renewable energy generation.

Flores has a 15 kV AC radial electricity distribution system with 46 buses and 45 branches, as depicted in Figures 4-4 and 4-5. A majority of the load is concentrated in the town of Santa Cruz, with a large portion of electricity demand near the harbor, and the remaining load is scattered across the island. Due to the infrastructure in place, it is unlikely that the line flow limits will be reached. However, due to the radial topography of the system, if one of the line fails, it could lead to a blackout for a large portion of the community.

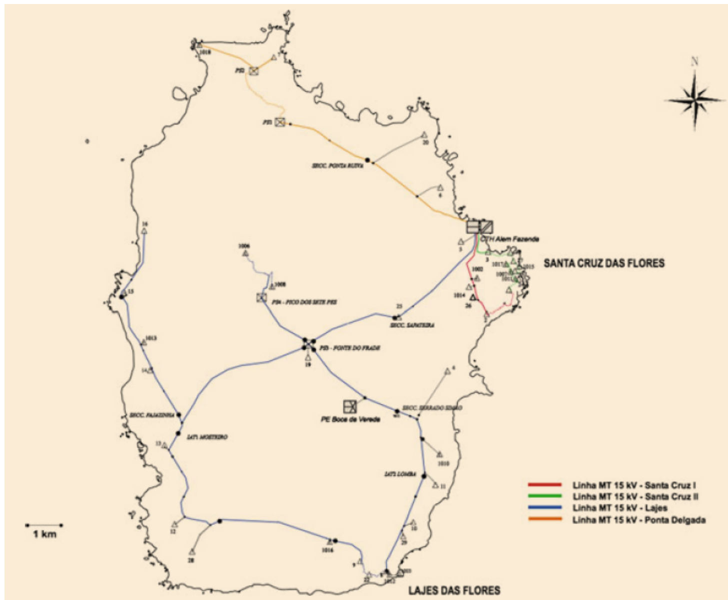


Figure 4-4: Electrical Network of Flores Island Ilic, Xie, et al., 2013

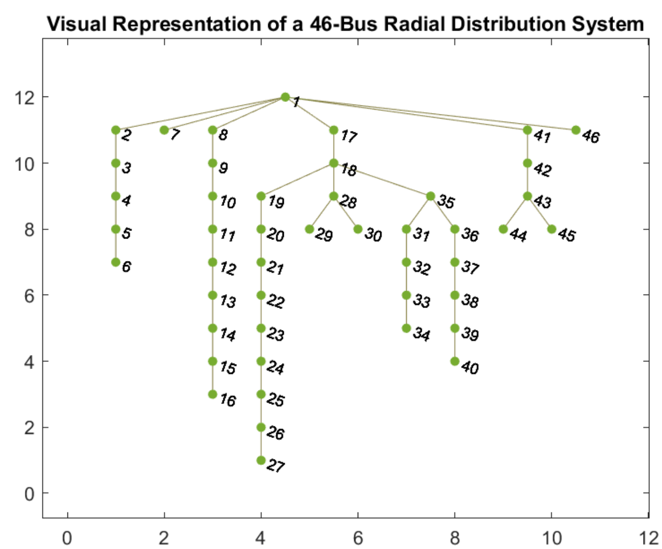


Figure 4-5: Topography of 46-Bus Radial Distribution System

Data

The main utility services of the islands, named Electricity of the Azores (EDA), provided load data and data on the generators for the year 2008. The load data are collected for the customers in 10-minute intervals. The spring months have the lowest peak load while the autumn months have the highest peak load. The customers demonstrate higher demand during weekdays and the lowest demand on Sunday.

Generation Data There are three generators across the system - at Node 1, Node 19, and Node 46. Four diesel generators, with a total capacity of 2.5 MW, provide 50% of the system's energy generation. Four hydropower plants, with a capacity of 1.65 MW, supply 35% of the island's energy. Finally, two wind power plants with a capacity of 0.65 MW, supply the remaining 15%. While the diesel plants and hydropower plants are close to the town of Santa Cruz, the wind power plants are located on a more isolated part of the island. The model of the wind power plants are Enercon E33 with a maximum capacity of 330 kW, and are opreated by GE Wind. The maximum output from the wind plants depend upon weather condition, and cannot be dispatched immediately, the wind power can be controlled quite quickly by the control center. The hydropower plant, with a reservoir of 50,000 m^3, has a slower activation time period. The diesel generator acts as the reserve energy source to balance supply and demand on a short notice. It is said that the diesel generators can be increased to maximum capacity within minutes.

The marginal cost of running the diesel plants are estimated using the spot market prices for fuel during 2008, while the marginal cost of the wind turbines and hydropower are considered to be negligible. However, instead of using the negligible marginal cost of the wind farm and hydropower, two synthetic cost functions were defined to capture a non-negligible cost of producing electricity at Node 19 and Node 46 at a higher price.

Load Data The EDA has several different tariff structures - medium voltage and low voltage. The medium voltage tariff is intended for commercial and industrial customers, while the low voltage tariff is for residential customers. The normal low voltage customers have three tariff structures to choose from; including a simply, flat-rate, a two-block, and three-block tariff. The flat-rate charges one price for every hour of the day. The two-block tariff has one price for peak-periods and off-peak periods of the day. Finally, the three-block tariff has a price specifically for peak, mid-peak, and off-peak periods. The times that each of these respective blocks refer to are very specifically chosen by the temporally diverse energy usage for each season. EDA charges for both energy and capacity. For the medium voltage customers, EDA also charges for reactive power supplied and received.

4.5 Estimating Electricity Demand Functions

While the 'cost functions' for each node in Section 4.3 were created using synthetic data, the Flores System provides an opportunity to test cost and benefit functions with more significance. In this case, the consumer's benefit function was modeled using basic economic theory behind estimating a consumer's demand function. Inverse demand functions are generally defined with the form P(Q) = a*Q + b, where P is the price per unit ($\$/MWh$) while Q is the quantity consumed (MWh), where a is a negative coefficient and b is positive. The integral of the inverse demand function represents the benefit function, as depicted in the bottom graph of Figure 4-6(a). In this case, $Benefit(Q) = \frac{1}{2}aQ^2 + bQ$, which would be concave down given the sign of a, and assuming that the constant value, c, is negligible.

However, in this algorithm, a positive X_i, implies power generated and a negative X_i signifies power consumed. The traditional inverse demand function and benefit function must be redefined to account for this alternative sign convention. Under this sign convention, in order to represent the same inverse demand curve, the formula would be rewritten as such: P(Q) = a'Q + b, where a' = -a, and b = b, as shown in the top graph of Figure 4-6(b). Furthermore, customers have rooftop solar energy in some of the simulations. In principle, a customer's total energy generation could be greater than the customer's total energy consumption. Therefore, during some hours of the day, the customer with rooftop solar could be a net generator, whereas it could be a net consumer during other hours. The top graph of Figure 4-6(b) demonstrates an example of an inverse demand curve for a customer which could be a consumer or a generator, which is why the function exists when Q is both negative and positive.

The integral of this inverse demand function given the new sign convention would result in the opportunity cost function. The bottom curve of Figure 4-6(b) represents the opportunity cost function, $Cost(Q) = -\frac{1}{2}aQ^2 + bQ$. As described by Hug et. al, this alternative sign convention provides a useful advantage of using this sign convention is that all of the power injections and power consumption sum to zero; $\sum_{i=1}^{N} x_i = 0$ (Hug et al., 2015).

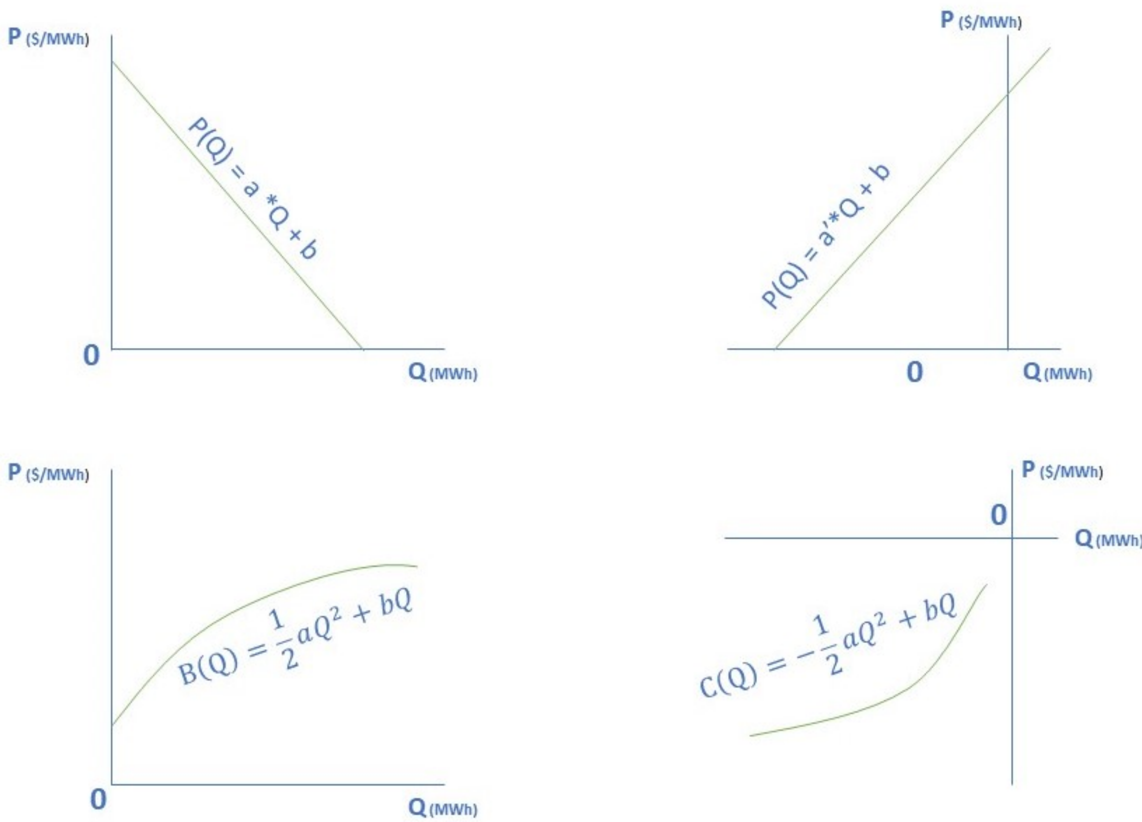


Figure 4-6: Economic Intuition Behind Cost Functions with (a) Positive Q implying consumption and (b) Negative Q implying consumption (Hug et al., 2015)

The linear term, b, from the aforementioned equation is estimated using a slope from the definition of price elasticity of demand, as displayed in Equation 4.6. The quadratic term, a, is estimated to be 0.001. Therefore, the cost functions for all of the customers are estimated to be that shown in Equation

4.7.

$$\epsilon_d = \frac{\frac{dQ}{Q}}{\frac{dP}{P}} = \frac{dQ}{dP}\frac{P}{Q} \tag{4.6a}$$

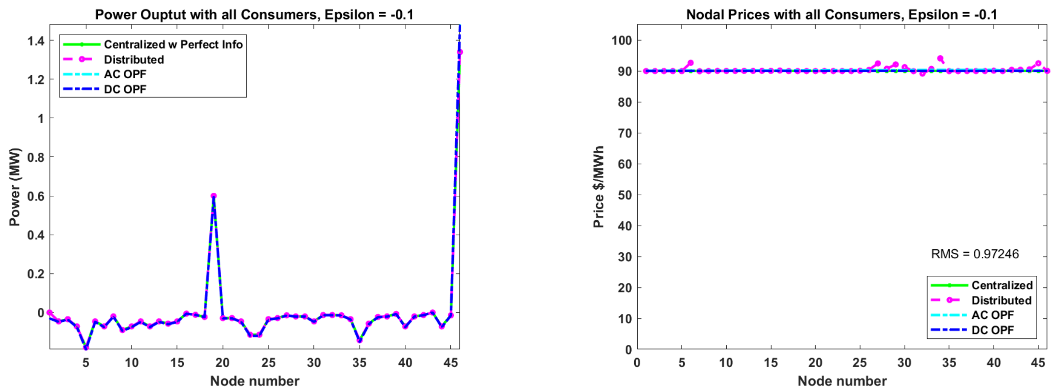
$$b = \frac{dP}{dQ} * \epsilon_d = \frac{\epsilon_d}{P_{avg}} Q_{avg} \tag{4.6b}$$

Energy economists have been exploring different ways to quantify the demand elasticity of electricity for decades. The value varies depending on the location, climate, income level, season, and type of devices used by the end-user. The literature typically uses a value between -0.1 and -0.3 (Burger, Christopher Knittel, et al., 2019). In the following sections, some cases test both values of elasticity, while other cases deliberately set a higher demand elasticity for some customers and a lower value for other customers.

$$C(Q) = 0.001Q^2 - \frac{1}{2}(\epsilon_d)\frac{P_a vg}{Q_a vg}Q \tag{4.7}$$

4.5.1 Power Dispatching and Nodal Prices under Varying Levels of DERs

In order to evaluate the accuracy and effectiveness of the decentralized algorithm proposed, the power dispatch and nodal prices are solved for under varying levels of DERs for one average hour of the year. There are multiple cases presented in this section: All consumers, Half Rooftop PV, Half Rooftop PV and Different Half EV, Same Half have PV and EV, All PV, and All Rooftop PV and All EVs. Under each scenario, the power dispatched and nodal prices are solved for using several different approaches. Each case is run using the centralized algorithm with perfect information of the customers, including each customer's benefit function. Each scenario is also dispatched using the decentralized algorithm outlined in the previous section. Finally, each scenario is solved for using the power systems software MATPOWER, which only has data regarding the generators and historic load data. The purpose of this exercise is to demonstrate that the centralized algorithm with perfect information and the decentralized algorithm converge to the same outcome, and that the DC OPF with imperfect information dispatches at different quantities. In addition to the power dispatching, the nodal prices for these different methods are also displayed under the following scenarios. The nodal prices are the Lagrangian term outlined in Equation 4.4, solved for on the downwards sweep of the algorithm.

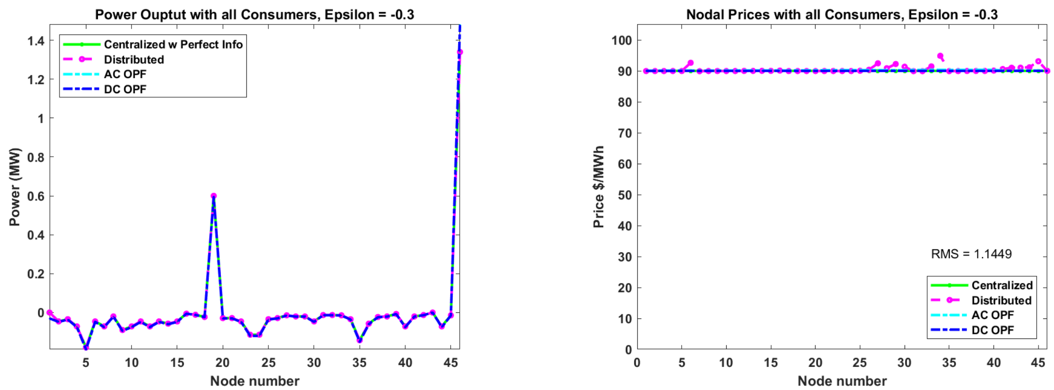


(a) Power Dispatched **(b)** Nodal Prices

Figure 4-7: Power dispatched and nodal prices under the case where all of the customers are purely consumers and have an $\epsilon_d = -0.1$

All Consumers In the first case, the three generators are producing electricity for the remaining 43 nodes, and there are no distributed energy resources. Thus, all of the consumers are purchasing electricity from the three generators. The power dispatched and nodal prices are displayed in Figure 4-7. Several interesting observations can be drawn from these graphs. The centralized economic dispatch with perfect information of consumer demand functions, decentralized algorithm, DC OPF, and AC OPF all lead to the same power dispatched across all of the customers and generators. The peaks at Node 19 and Node 46 signify the power injected by the generators at Node 19 and Node 46. The generator at Node 1, the most expensive generator of the three, is not dispatched and thus remains zero. The remaining nodes are customers and are consuming load, which is why the values for power output are negative. In the first scenario with all consumers, both DC OPF and AC OPF are compared, and demonstrate the same solution In practice, market operators typically use DC OPF, and therefore only DC OPF will be considered in the following cases. Figure 4-7**(b)** also shows that the nodal price remains close to $90 / MWh, which is the marginal cost of the marginal centralized generator.

In order to visualize the impact of the demand elasticity on the power output of the system, the power dispatching and nodal prices are displayed when ϵ_d = -0.1 and ϵ_d = -0.3. As seen in Figure 4-7 and Figure 4-8, the power dispatching and nodal prices are not impacted drastically by the increase in demand elasticity when every customer is purely a consumer. This is because an increase in the demand elasticity represents a rotation of the demand curve around the utility-maximizing quantity of demand for each household, by construction. Thus, for future scenarios, the demand elasticity is assumed to be -0.1 unless otherwise specified. However, the demand elasticity is adjusted in future scenarios when customers own flexible load, such as electric vehicles. The varying levels of demand

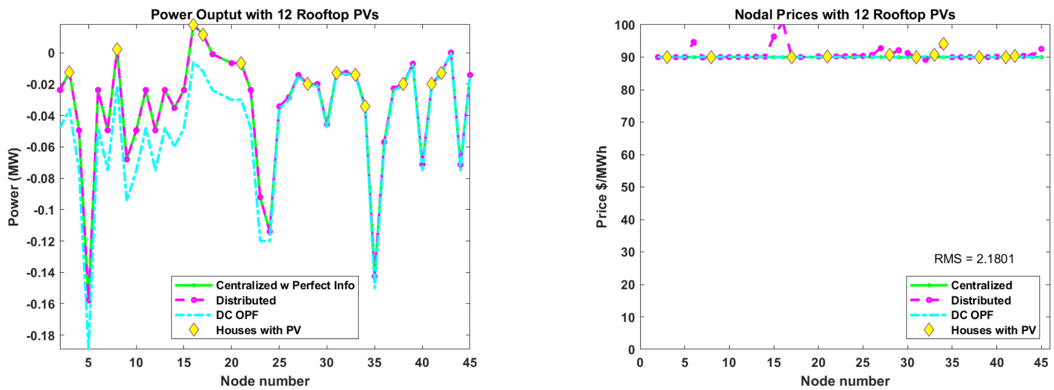


(a) Power Dispatched **(b)** Nodal Prices

Figure 4-8: Power dispatched and nodal prices under the case where all of the customers are purely consumers and have an $\epsilon_d = -0.3$

elasticity are also important and impact the results in **Chapter 5**.

Half Residential Households Deployed Rooftop PV Under the first scenario with DERs, some residential customers, randomly selected from the 23 residential end-users, installed rooftop PV. A moderate increase in solar energy capacity is assumed to be 1.12 MW for the entire island. Using solar radiation data from 2009, the average solar radiation is estimated implies a capacity factor of approximately 0.246. Thus, ignoring the orientation and spatial diversity among the residents, the 0.276 (MW) of average solar energy is evenly distributed among the randomly selected residents. In order to account for the generation from the rooftop solar panels throughout the simulation, the historic loads, demand functions, and P_{min} and P_{max} are all updated accordingly. In other words, the difference between the initial load at that node with the expected energy provided by the solar panels is used throughout the simulation instead of the initial load itself. This allows some customers to be net producers as they contribute their surplus energy as a source of energy for the community to meet its total energy demand. The power dispatched and nodal prices for the scenario where 14 residential customers have rooftop solar are displayed in Figure 4-9. In order to display the differences in power dispatched across the algorithms, the power dispatched is only shown for the consumers, rather than including the generators as was shown in previous graphs. It is clear that the power dispatched is consistently converging with the solution obtained when the centralized algorithm is used with perfect information of customer preferences across the cases. The nodal prices vary slightly from the centralized algorithm in this case, which is due to slight numerical errors. In practice, the system operator uses optimization software that is very advanced and robust, which should be able to eliminate these small numerical



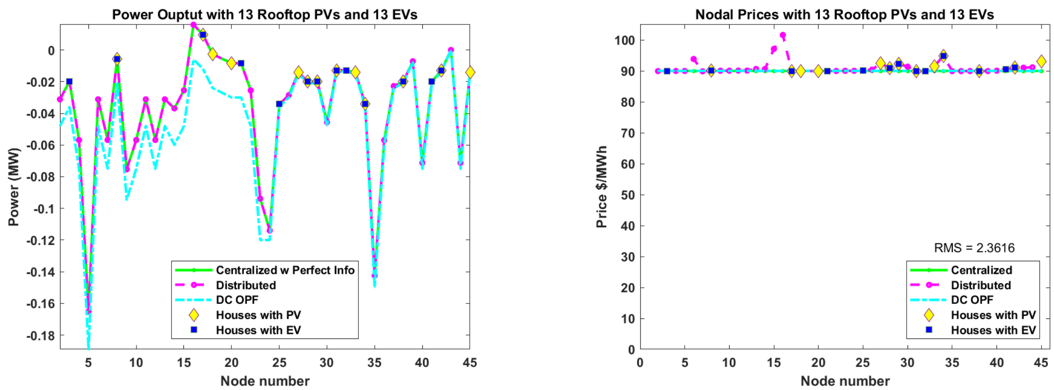
(a) Power Dispatched **(b)** Nodal Prices

Figure 4-9: Power dispatched and nodal prices under the case where half of the randomly selected residents have solar PV

issues.

The disparity between DC OPF and the decentralized algorithm is noticeable in this scenario, which would lead to both a technical and economic inefficiency. The larger the difference, the more power that is being dispatched by the centralized operator that is not required by the community. Thus, using the decentralized algorithm could lead to cost savings for the community.

Half Customers Randomly Selected to have PV, Half Customers Randomly Selected to have EVs
In this case, half of the residential customers were randomly selected to have rooftop solar and half of them were randomly selected to have electric vehicles. While some of the customers overlap, there are some customers that have surplus energy from the rooftop solar while other customers have higher demand associated with EV charging. Electric vehicles are one example of a flexible load, which means that the time of use is flexible. Various models account for these appliances by shifting the flexible load towards a period that is more suitable for the system - this could be to smoothen out load curves or to maximize the use of renewable energy. While demand management systems are being explored in other research areas, here we model the ownership of an electric vehicle by increasing the demand for electricity for the appropriate household, but also increasing the demand elasticity to to -0.3 accordingly. The output of this scenario, displayed in Figure 4-10, leads to similar results, where the centralized algorithm with perfect information and decentralized algorithm converge to the same solution for both the power dispatched and the nodal prices.



(a) Power Dispatched

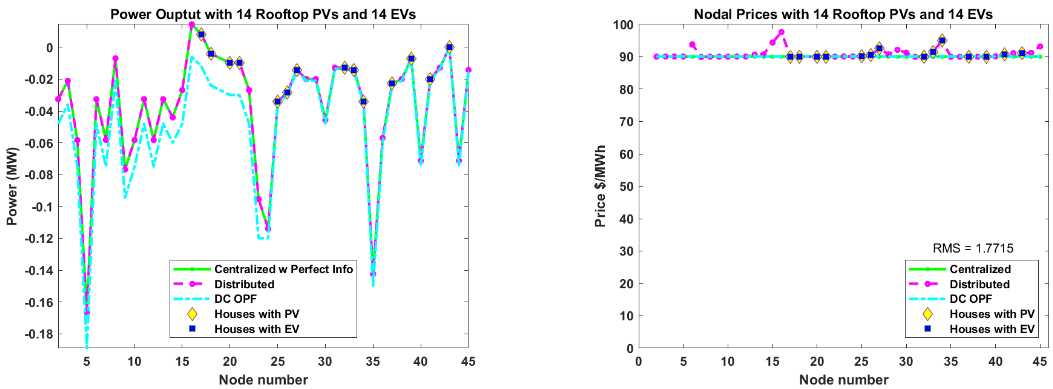
(b) Nodal Prices

Figure 4-10: Power dispatched and nodal prices under the case where half of the randomly selected residents have solar PV and half were randomly selected to have EVs

Half Customers Randomly Selected to have both PV and EV This case varies slightly from the previous one in that the same customers that have rooftop solar also own electric vehicles. Therefore, they are producing energy using the rooftop solar, and their load increases due to the electric vehicles. These effects essentially cancel the other one out, which is why the decentralized dispatches power at levels more similar to the DC OPF than in the previous case. The neighbors are no longer trading energy, but instead using their surplus electricity to charge their electric vehicles.

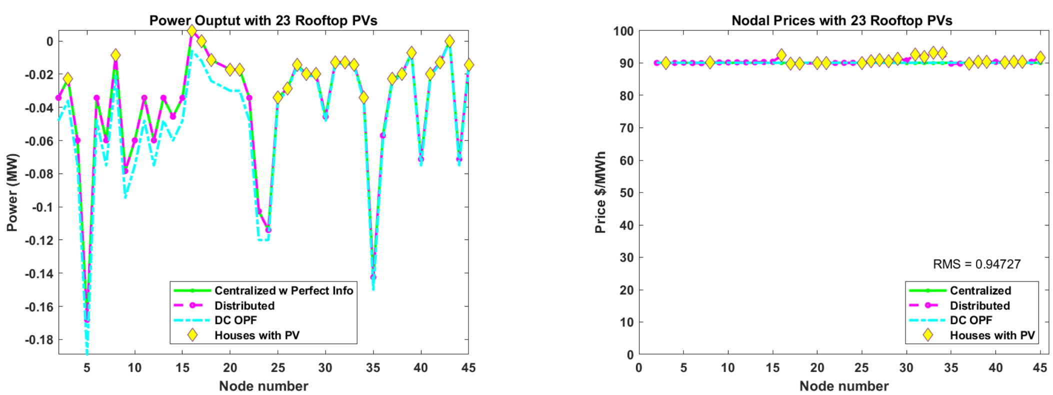
All Residential Customers have Rooftop PV Under this scenario, all of the residential customers have rooftop solar. The power dispatched and the nodal prices are displayed in Figure 4-12. As previously displayed, the centralized algorithm with perfect information and decentralized algorithm converge to the same power dispatched - for customers with and without solar PV.

All Residential Customers have Rooftop PV and an Electric Vehicle Under the final DER scenario, each residential customer has both rooftop solar panels and an electric vehicle. Since each residential household is both producing electricity, with rooftop solar, and consuming more electricity, due to the electric vehicles, the load demanded by the network is roughly the same as the case with no DERs. Thus, the dispatching between DC OPF and the decentralized algorithm with knowledge on the customer's demand function lead to a very similar output.



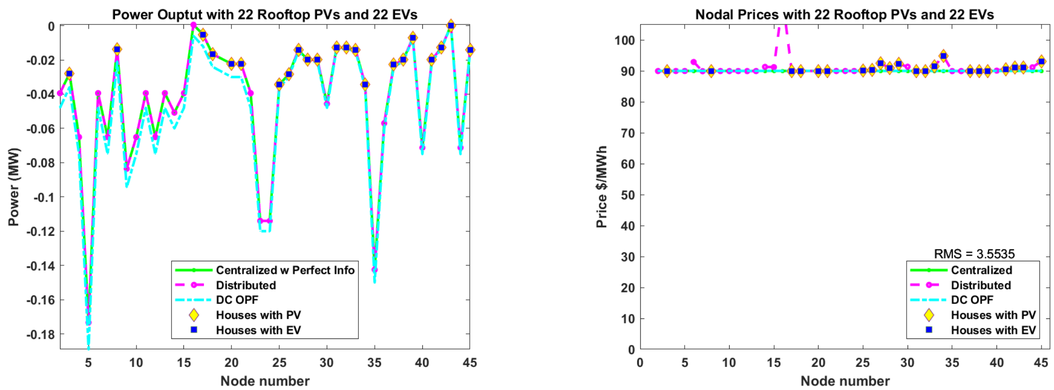
(a) Power Dispatched **(b)** Nodal Prices

Figure 4-11: Power dispatched and nodal prices under the case where half of the randomly selected residents have both solar PV and EVs



(a) Power Dispatched **(b)** Nodal Prices

Figure 4-12: Power dispatched and nodal prices under the case where All Residential Customers have Rooftop PV



(a) Power Dispatched

(b) Nodal Prices

Figure 4-13: Power dispatched and nodal prices under the case where All Residential Customers have Rooftop PV and Electric Vehicles

4.5.2 Advantages of Decentralized Algorithm

By taking advantage of the radial structure, the algorithm allows for local information exchange in order to enable computationally feasible energy exchange (Jaddivada et al., 2019). The use of local data exchange provides an opportunity to reach the same solution without expecting a centralized system operator to have knowledge on the entire system. The Distributed OPF algorithm defined in this paper would be able to capture the heterogeneous demand functions of various consumers, without excessive communication requirements.

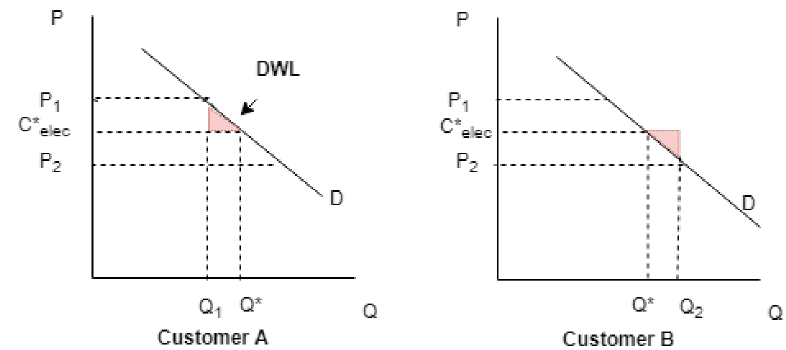
Chapter 5

Economic Implications

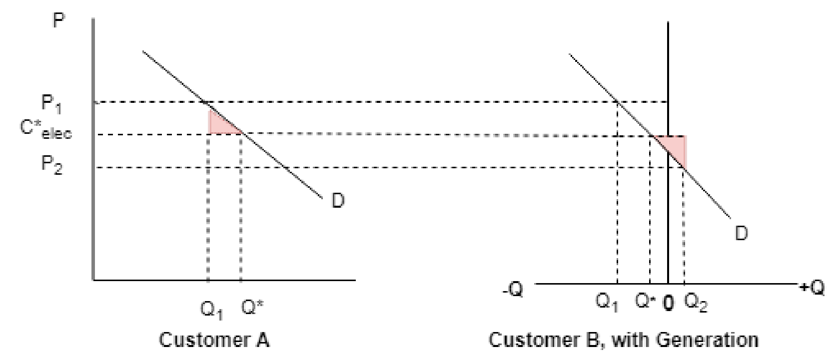
5.1 Theoretical Economic Benefits of Energy Transactions

As aforementioned in **Chapter 1.4**, improper electricity signals lead to a loss of social welfare. Currently, one of the most economically efficient pricing structures in practice is real-time pricing, which uses the LMP, calculated on the transmission level, to charge the customer an hourly energy price (Burger et al., 2019). As distributed generation is becoming increasingly spread out across the system, most utilities use net metering to account for any surplus energy injected back into the grid. Incumbent net metering policies essentially reduce the monthly electricity bill of a customer with distributed generation, but do not properly account for the impact of the injected surplus onto the system. For example, net metering with a flat rate tariff does not acknowledge the temporal impact or spatial impact of electricity injection on the system. Furthermore, net metering with RTP still does not properly address the spatial granularity of hourly prices across the electricity system, because the LMP used for RTP is calculated for the nodes on the transmission level, but does not go down to the distribution level.

Ideally, the energy provider could calculate the DLMP on an hourly basis, and use the DLMP as one part of a three-part tariff, in addition to fixed network costs and a capacity charge. This would allow the prices faced by the consumer to account for the temporal and spatial granularity across the system.



(a) Two Customers With Diverse Prices



(b) Two Customers With Diverse Prices, Customer B has DG

To demonstrate the impact of inefficient pricing, let us consider two customers with similar demand functions and consuming all of their energy from the utility company, but face different inefficient prices. Customer A is charged P_1 and Customer B is charged P_2. However, the true cost of producing electricity is labeled as $C*_{elec}$. The deadweight loss (DWL) in this scenario is signified by the red triangles in Figure 5.1(a). For Customer A, the DWL is the area under the demand curve and above $C*_{elec}$, because the consumer is consuming less than the optimal amount. For Customer B, the DWL is the area below $C*_{elec}$ and above the demand curve, because Customer B is consuming more than the optimal amount.

Now, let us consider two consumers, where Customer B has installed distributed generation (DG). Customer A is still charged P_1, despite the incorrect pricing. Since Customer B has installed DG in this case, the DG simply shifts the demand curve to the left, but the elasticity of the demand function remains unaffected. Thus, the graph on the right side of Figure 5.1(b) has both -Q and +Q. In this example, a negative Q refers to the amount of energy that Consumer B sells back into the grid, while the positive Q still signifies the amount of energy purchased and consumed by Customer B. C_{elec} signifies the average cost of producing electricity.

In the case of Scenario (b), under market equilibrium, Consumer A should be able to purchase electricity at the price of C_{elec} and Consumer B should be able to sell its surplus electricity at a price of C_{elec}. If the price is set to be P_1, which is too high, then Consumer B will theoretically sell more than it should into the system, Q_1, than the optimum amount Q*. In contrast, if price is set to P_2, which is too low, then Consumer B is incentived to consume more electricity than optimum, and will not inject any surplus into the system. Thus, the improper price signals affects whether Consumer B is consuming or producing more energy than the optimal amount, whereas Scenario (a) only affects the total consumption of each consumer.

5.2 Analyzing the Change in Welfare

In addition to proving that the decentralized algorithm converges with the centralized algorithm with perfect information, in **Chapter 4**, the economic implications of the decentralized algorithm are explored here as well. The impact on charging the customer the nodal price that is solved for with the decentralized algorithm, when compared with the nodal price that is the outcome of the DC OPF, should lead to a net change in welfare for the consumer. This section compares the economic impact of using the nodal price calculated with the decentralized economic dispatch with perfect information with the DC OPF which solely uses the cost functions of the three centralized generators. In reality, the 43 consumer nodes are categorized under varying tariff structures, and the price indicated by the DC OPF may not be the exact price of electricity that is charged for the customer. However, it remains a useful exercise to quantify the economic benefits from using the DLMP rather than the LMP solved for by the DC OPF.

Thus, the change in welfare is quantified for the consumers on Flores Island. The demand of electricity is modeled as an exponential equation dependent upon average prices and the elasticity of demand, as clearly listed in Equation 5.1(a) (Burger et al., 2019). Therefore, in order to calculate the change in welfare, the area under the demand curve is calculated by integrating the demand curve from each price up to the Value of Lost Load (VOLL). The welfare is calculated for the P_{DCOPF} and P_{decent}, and the percent increase between the two prices is displayed in Figure 5-1. In order to remain consistent with the literature, a VOLL of $9,000 was estimated for the purpose of calculating the change in welfare.

As expected, the customers that have flexible load such as electric vehicles, which have a higher demand elasticity, see a higher increase in welfare with the decentralized algorithm. Since the DC OPF approach

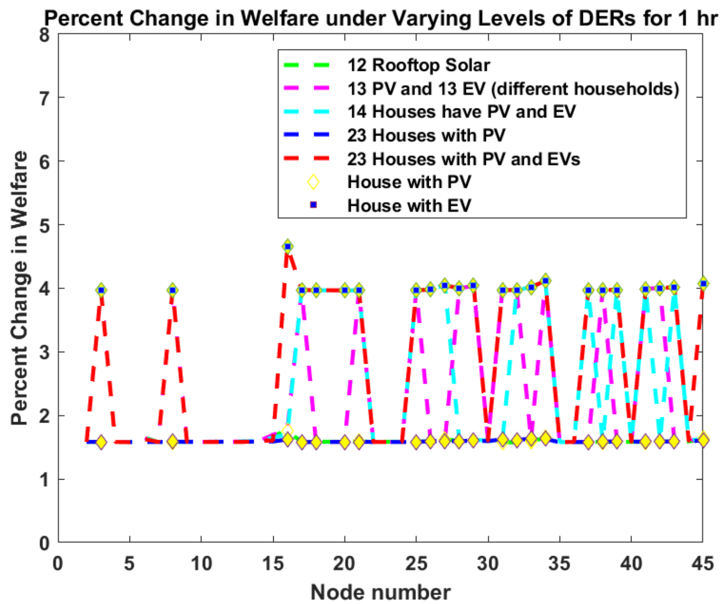


Figure 5-1: Visual Representation of Change in Welfare Under Varying Levels of DERs

assumes that each customer has a purely inelastic demand curve, the introduction of demand elasticity will increase the welfare for the more elastic consumers. This is the reason as to why the consumers with electric vehicles have higher percent change in welfare as compared to other customers. It is also interesting to note that the customers that had surplus energy from solar rooftop did not see such a high increase in welfare. Although the net metering policies are inefficient from the system's perspective, for not appreciating the temporal or spatial impact of injecting surplus solar energy into the system, the DLMP would not improve consumer surplus as much for customers with distributed generation as it would for those with flexible load. These results are useful, as they imply that the welfare will increase more for customers that have flexible load rather than distribution generation at the household level. This result may be different when considering the temporal impact of the decentralized economic dispatch algorithm. Therefore, the decentralized algorithm would improve overall social welfare when more customers have appliances such as electric vehicles, smart laundry machines, and other appliances that introduce flexible usage.

$$x' = x_{avg}\left(\frac{p'}{p_{avg}}\right)^{\epsilon} \tag{5.1}$$

5.3 Total Cost Under All of the Cases

In addition to the ability to charge the customer a more appropriate DLMP, the total energy dispatched by the centralized generators varies across the five explored scenarios when using the decentralized algorithm. Figure 4-7 through Figure 4-13 show how the generation under the DC OPF and the decentralized algorithm with perfect information dispatch different levels of power from the three centralized generators. This is shown by the gap between the DC OPF and the decentralized algorithm for all of the scenarios with DERs. Essentially, the DC OPF only uses the cost functions for the three centralized generators and assumes that each customer has purely inelastic demand functions, and therefore tends to dispatch more power than necessary. The decentralized algorithm accounts for the heterogeneous benefit functions for all of the customers, and accounts for the cost functions of the three centralized generators along with the cost of the distributed generation across the system. Therefore, the decentralized algorithm leads to cost savings by dispatching a more appropriate amount of power (i.e. less) from the three centralized generators and taking advantage of the cheaper energy supplied by rooftop solar.

Thus, the total cost of supplying electricity with the centralized and decentralized algorithms are compared for the five DER cases in Table 5.1. The second column represents the total cost of the three generators, along with the cost of the energy produced by DERs, which is calculated using the decentralized economic dispatch. The third column represents the total cost of producing energy calculated with the centralized DC OPF algorithm, which is over-dispatching energy in the cases with DERs. The savings column represents the difference between the centralized and decentralized algorithm, which could be the potential savings by using the decentralized algorithm with perfect information. The average savings for one representative hour is then scaled up to estimate the approximate annual savings across one year, which is represented in the final column of Table 5.1. Both the centralized and decentralized algorithms dispatch approximately the same amount of power in the scenario with no DERs, which is why this case leads to minimal cost savings.

As expected, the cost savings increase as more DERs are introduced across the system. In addition, the energy transactions lead to higher cost savings when the DERs are spread out across the customers. In one scenario, the solar rooftop and electric vehicles are randomly assigned across the system, whereas in another scenario, the same customers are assigned both rooftop solar and electric vehicles. In the case where the DERs are randomly dispersed, the decentralized algorithm allows the neighbors to trade energy with eachother, and therefore the decentralized algorithm leads to higher cost savings. In contrast, when half of the customers have both rooftop solar and electric vehicles, they do not gain as much value from the energy transactions. This is because the customers have higher load, due to the electric vehicle, but are also producing their own energy, with the rooftop solar, which is why the output is not as different from the solution obtained using the centralized DC OPF.

Therefore, comparing the total cost of producing electricity using the centralized and decentralized algorithms, it is clear that the decentralized approach could reduce future investments in generation capacity expansion and ultimately could reduce costs for the utility company and consumers alike. In some cases, not displayed here, the total energy supplied by the DERs could allow the system to meet their demands with a cheaper marginal generator with a lower marginal cost, which would set the equilibrium price to be considerably lower. Theoretically, this would lead to a larger amount of savings for the system.

Scenario	Cost with Decentralized Alg ($/MWh)	Cost with DC OPF ($/MWh)	Savings (1hr)	Annual Savings(1 year)
All Consumers	$ 1,256.60	$1,260.70	$4.10	$35,916.00
12 Houses with PV	$1,215.09	$1,260.70	$45.60	$399,456.00
13 Houses with PV, 13 Diff Houses with EVs	$ 1,224.39	$ 1,260.90	$36.51	$ 319,827.60
14 Houses with both PV and EV	$1,227.73	$1,260.70	$32.96	$288,729.60
23 Houses with PV	$1,234.92	$1,260.70	$25.77	$225,745.20
23 Houses with both PV and EV	$1,245.32	$1,260.70	$15.37	$134,641.20

Table 5.1: Total Cost of Producing Energy when using Centralized and Decentralized Methods

Chapter 6

Conclusion

Inefficient electricity tariffs have persisted through the restructuring of electricity markets despite ample recommendations of alternative designs. Due to the lack of incentives, exacerbated inefficiencies due to DERs, and lack of success with other policy measures, a technical approach such as the implementation of distribution system operator could serve as a way of moving towards efficient electricity pricing. Since the United States is spending heavy investments across the transmission and distribution system, now is a perfect time to implement recent innovations such as urban microgrids with advanced metering infrastructure and a variety of distributed energy resources. With access to a higher granularity of data, a distribution system operator could implement a more innovative tariff structure that incorporates an hourly DLMP. The urban microgrid could potentially run like a cooperative and find the optimal solution for the specific community it serves. In order to move towards this solution, local and state regulators should be more encouraging of such pilots. Investor-owned utilities should continue to explore the potential relationship between the distribution system operator, as some progressive utilities have begun doing. Ultimately, this progressive business model could help the electricity industry move towards more efficient electricity pricing along with being better prepared for increased DER penetration.

As more customers will be purchasing DERs, such as rooftop solar, and flexible load, such as electric vehicles, alternative market structures are proposed which allow for energy transactions between the customers and generators of the system. Current approaches for optimizing power dispatched in a decentralized manner, while allowing for energy transactions, have introduced computational and numerical challenges. Thus, this thesis introduces an alternative approach to solving for the decentralized economic dispatch, which is then tested on an 8-Bus proof-of-concept example. In order to further demonstrate the viability of using a decentralized algorithm to dispatch electricity across heterogeneous customers, the algorithm is tested on a radial distribution system in Flores using real data. The solution obtained with the decentralized algorithm is compared with the solution solved for with the top-down centralized algorithm for various levels of DERs.

Finally, the economic implications and cost savings are studied in order to quantify the economic benefits of approaching electric distribution systems from a more bottom-up, decentralized perspective. The economic analysis implies that the decentralized algorithm would improve welfare for customers with higher demand elasticity, such as customers with flexible load. Overall, the use of the decentralized algorithm to dispatch power for a radial electricity system could lead to cost savings between approximately $35,000 and $400,000 per year. These cost savings could be attributed to the decentralized algorithm accounting for the cost of distributed energy resources and the demand elasticity of consumers.

6.1 Future Work

While the decentralized algorithm to dispatch electricity accounting for heterogeneous demand functions and system constraints was displayed for one time period, the temporal effects of using the algorithm would display its true economic advantages. For example, if community members could dispatch their flexible load according to the day-ahead electricity schedules, this could take advantage of low prices and wind energy at the nighttime. Alternatively, modeling storage options into this model would also introduce a number of economic benefits by shifting load to periods of lower prices and communicating preferences in order to lead to system efficiency. It would be very helpful to communicate the DLMP to home storage systems, such that they could operate accordingly. Furthermore, in the long run, the community could choose to move forward by using energy savings and concurrent cost savings to contribute to a larger communal investment, such as a storage unit that could be used by multiple households. These are just a few examples of how the temporal impact of the same algorithm could lead to interesting results and discussions.

6.2 Relevance

In response to recent climate change predictions published by the Intergovernmental Panel on Climate Change, it is of the utmost importance to accelerate the process of decarbonizing the electric grid. This intimidating endeavor must be tackled from several different perspectives, such as improving energy efficiency and demand response efforts to reduce electricity demand, integrating in more renewable energy through distributed and centralized resources, and supplying low-carbon base load. Every effort to decarbonize power systems contributes to the collective efforts of mitigating climate change.

In addition to encouraging renewable energy through policy measures, the implications of renewable energy and electrification of the transportation sector on the infrastructure itself - namely transmission and distribution systems - must be carefully studied and accounted for. The use of a distribution system operator with energy transactions is one possible way in which electricity systems may evolve in response to these large industry-wide transitions. A recently published report from the International Renewable Energy Agency (IRENA) emphasized the importance of allowing "distribution companies to interact more often with distributed energy resources to efficiently manage network constraints by facilitating the participation of distributed flexibility resources into energy markets, thereby promoting an increase in renewable energy shares" (IRENA, 2017). However, the industry is not moving in this direction with an adequate sense of urgency. By researching and evaluating innovative approaches to manage distribution systems, instead of expecting the traditional, top-down approach to be the most efficient solution, this thesis seeks to accelerate progress towards a cleaner future.

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